

Use of models in study design for dynamic systems: Ebola vaccine trial design

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DAIDD

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White Oak Conservation

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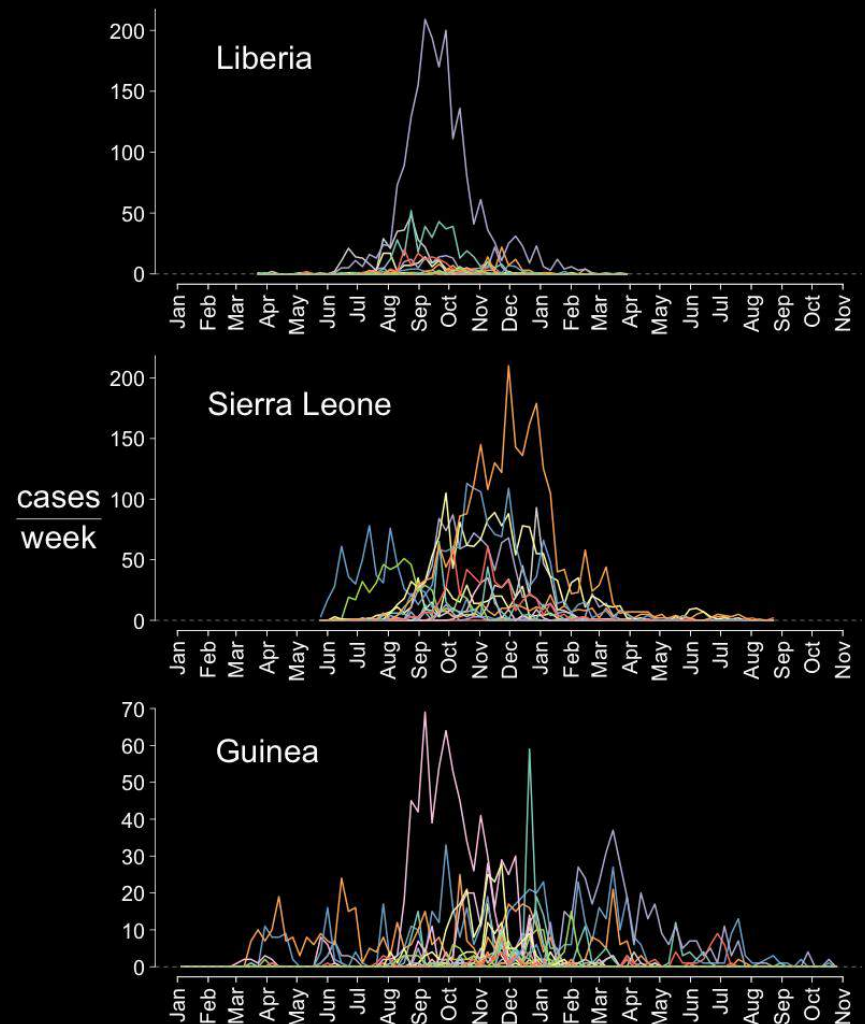
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Goals

- Understand data-centric and process-centric perspectives.
- Learn how simulation can guide trial design

The West African Ebola Epidemic

- What processes **drive** the epidemic?
- Who is at **highest risk**?
- When will it **peak/end**?
- Which **interventions** work?
- **Optimal allocation** of sparse resources?



Infectious Disease Research

Logistical, financial and ethical constraints
limit quantity & quality of data



Perspectives from Two Disciplines

Classical Epidemiology

Data-Centric

(Public Health)

Risk Factors

Biostatistics

Mechanistic Epidemiology

Process-Centric

(Disease Ecology)

Infectious Disease Dynamics

Mathematical Modeling

Classical Epidemiology

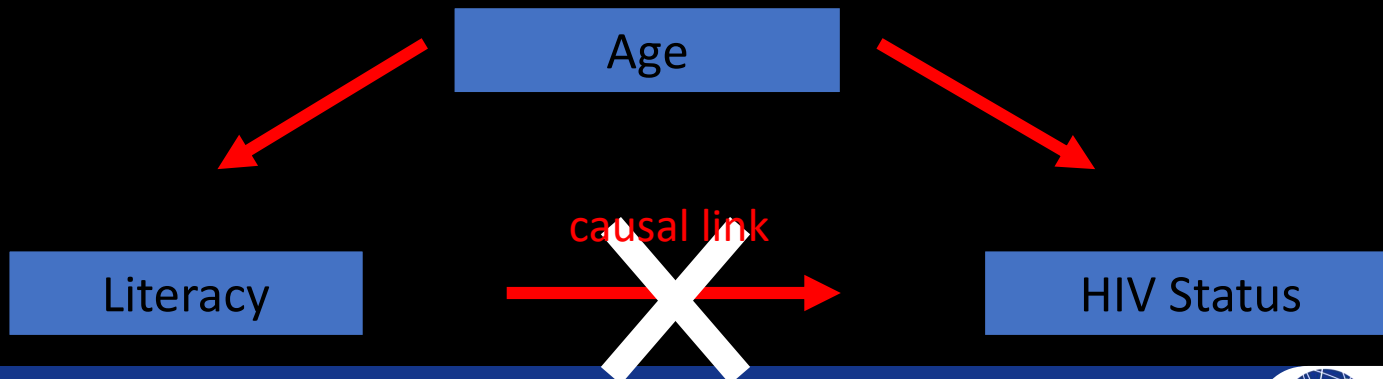
- Does A cause B?

Classical Epidemiology

Individual	Literate	HIV infected
1	0	0
2	0	0
3	0	0
4	0	1
5	1	1
6	1	0
7	1	1
8	1	1

- Does literacy cause HIV?
- Find **correlations that imply causality** by accounting for

1. random error: do we have enough data?
2. bias: are design & analysis valid?



Classical Epidemiology

Infer causation via carefully identified correlations

Minimize bias via:

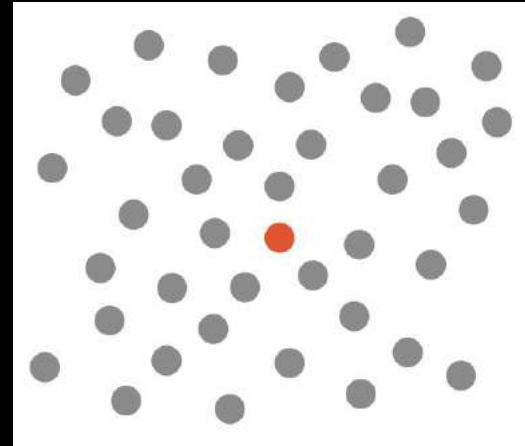
- **study design**: e.g. randomization, blinding
- **analytical methods**: e.g. causal inference modeling

What do *Introductory Epidemiology* courses teach?

- Measures of Disease
- Measures of Effect (of a risk factor)
- Study Designs for Measuring Effects
 - Dealing with random error
 - Dealing with confounding
 - Dealing with bias
- Biostatistical analyses for analyzing data

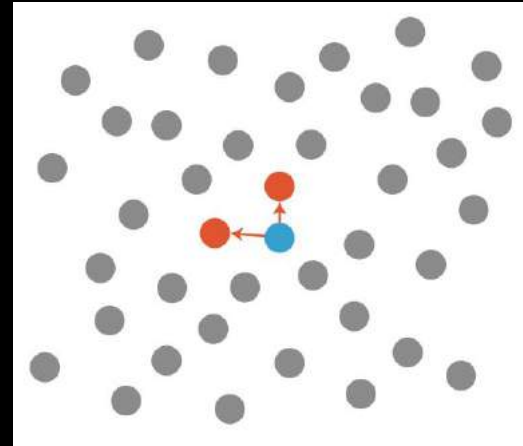
Mechanistic Epidemiology

- Scale up from individual processes to population patterns



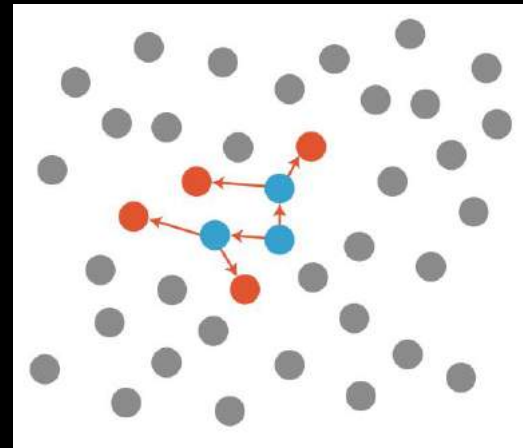
Mechanistic Epidemiology

- Scale up from individual processes to population patterns



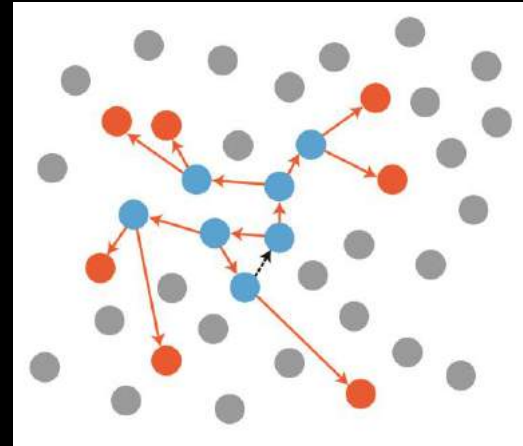
Mechanistic Epidemiology

- Scale up from individual processes to population patterns



Mechanistic Epidemiology

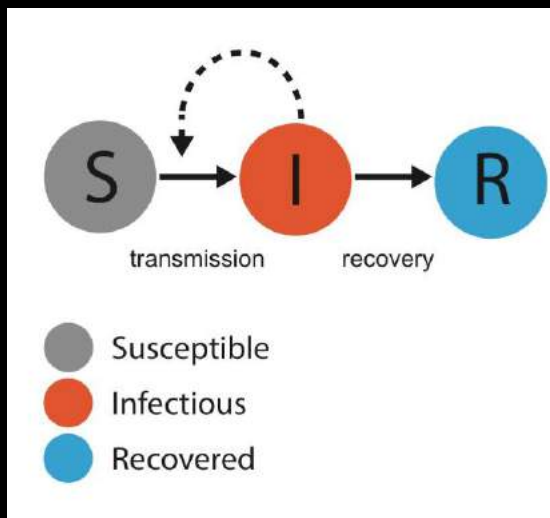
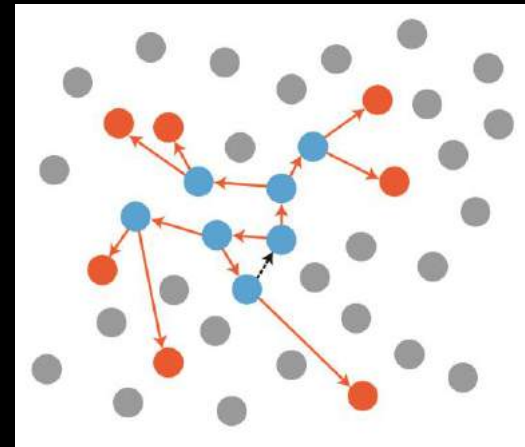
- Scale up from individual processes to population patterns



Mechanistic Epidemiology

- Scale up from individual processes to population patterns

solid arrow = flow between disease states
dashed arrow = influence

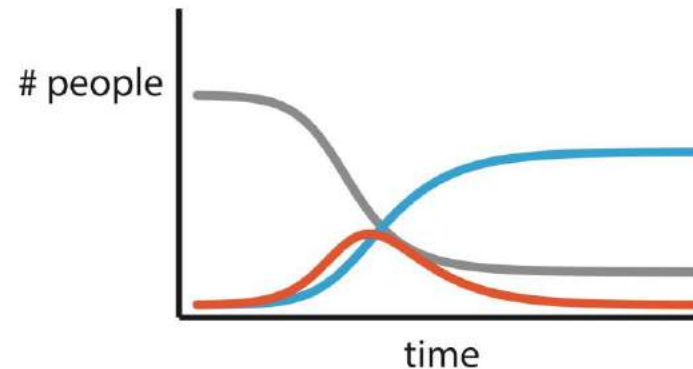
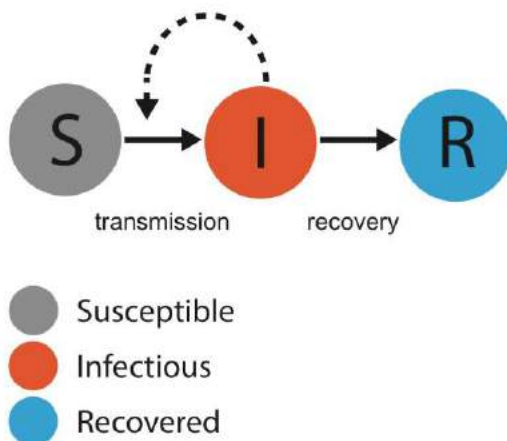
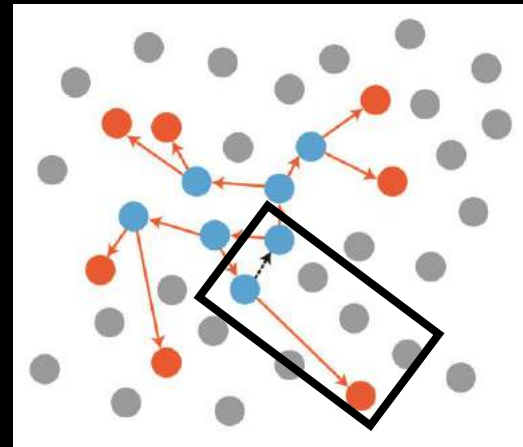


How do contact processes
cause epidemics?

Mechanistic Epidemiology

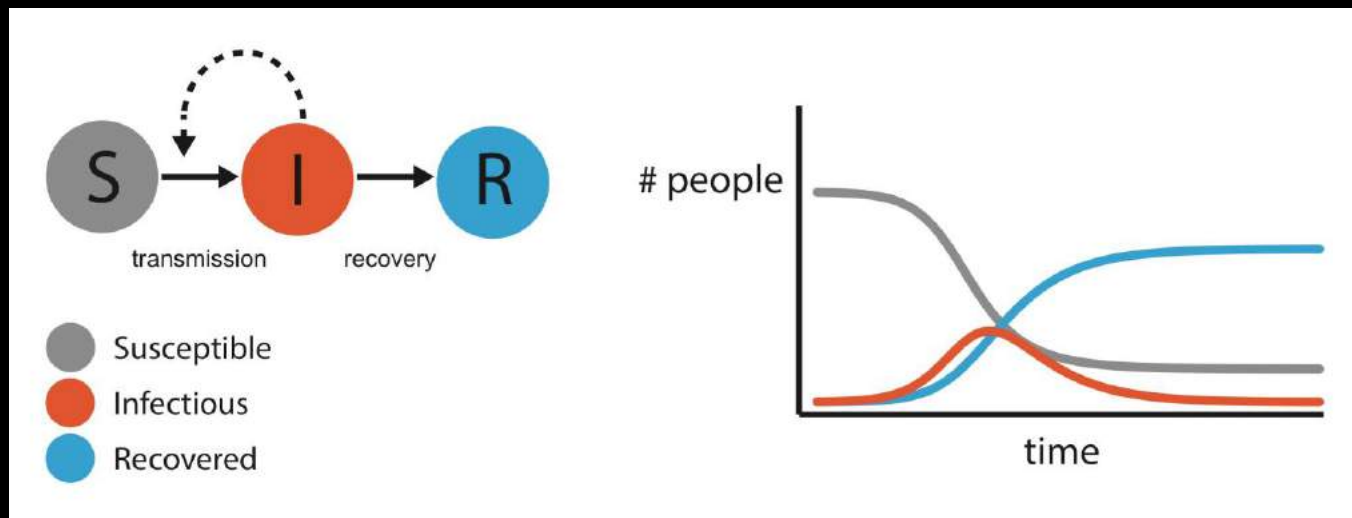
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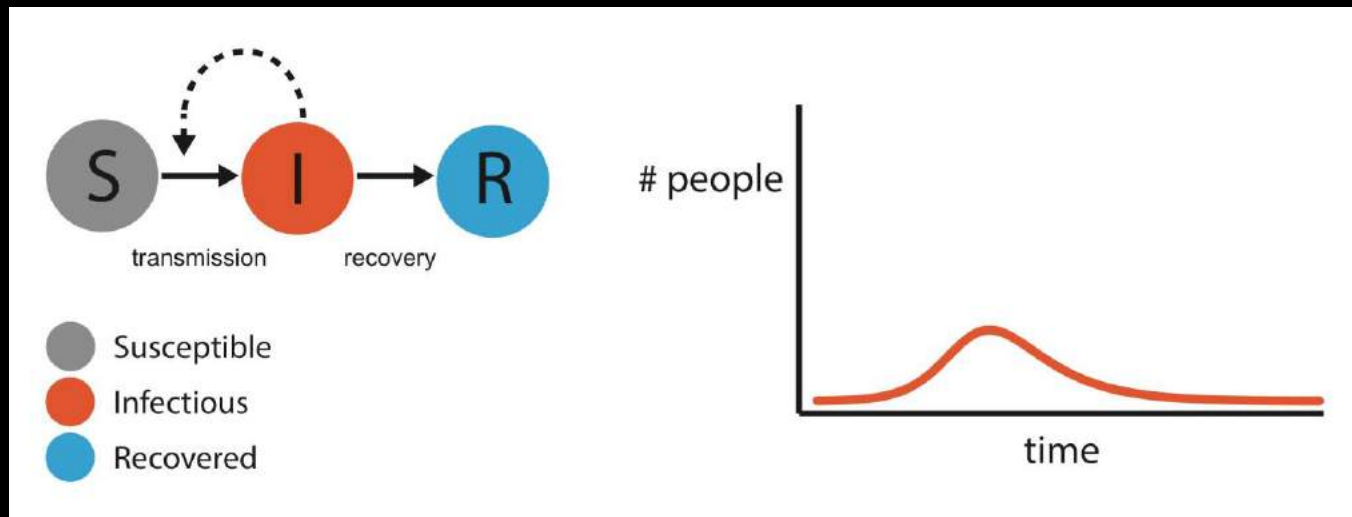
Mechanistic Epidemiology

- Scale up from individual processes to population patterns
- “What if” scenarios not amenable to experimentation



Mechanistic Epidemiology

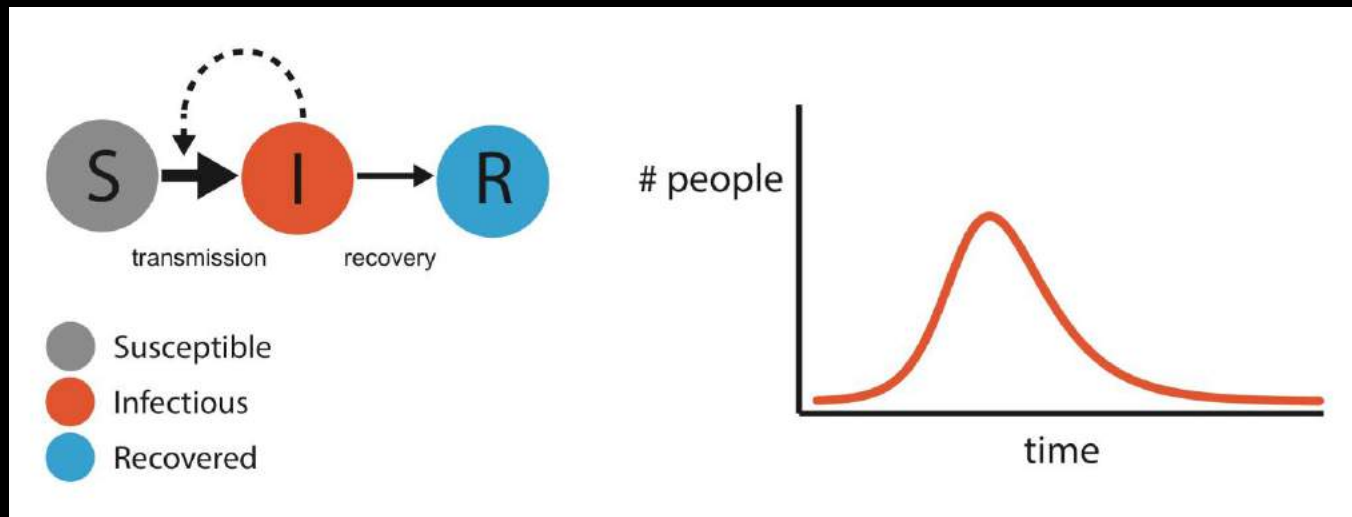
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Mechanistic Epidemiology

- Scale up from individual processes to population patterns
- “What if” scenarios not amenable to experimentation

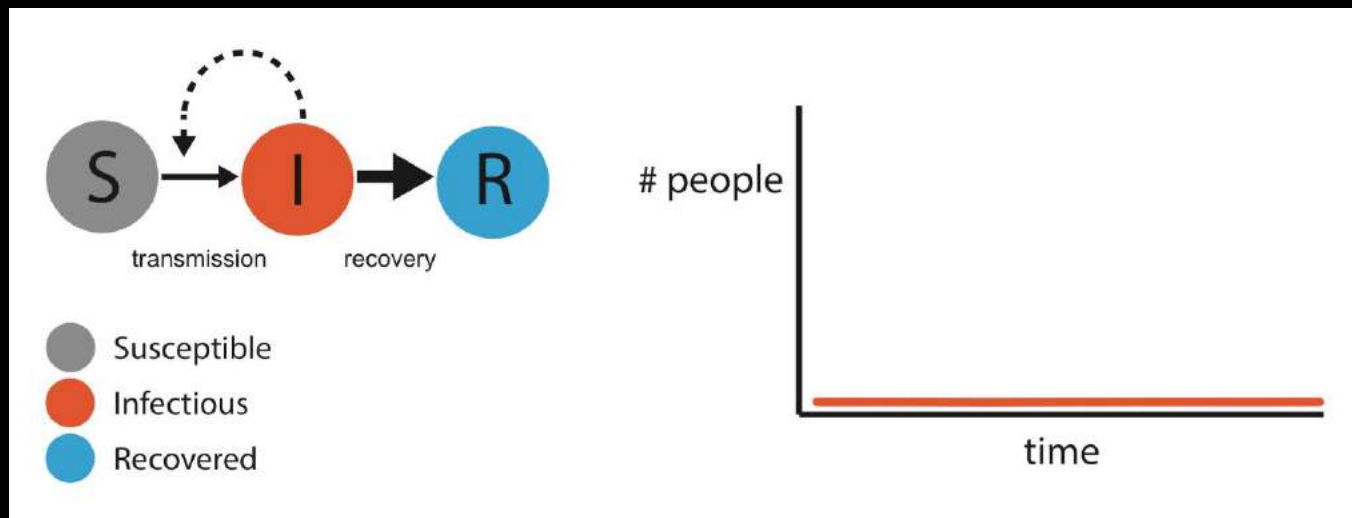
What if each person exposed 50% more people?



Mechanistic Epidemiology

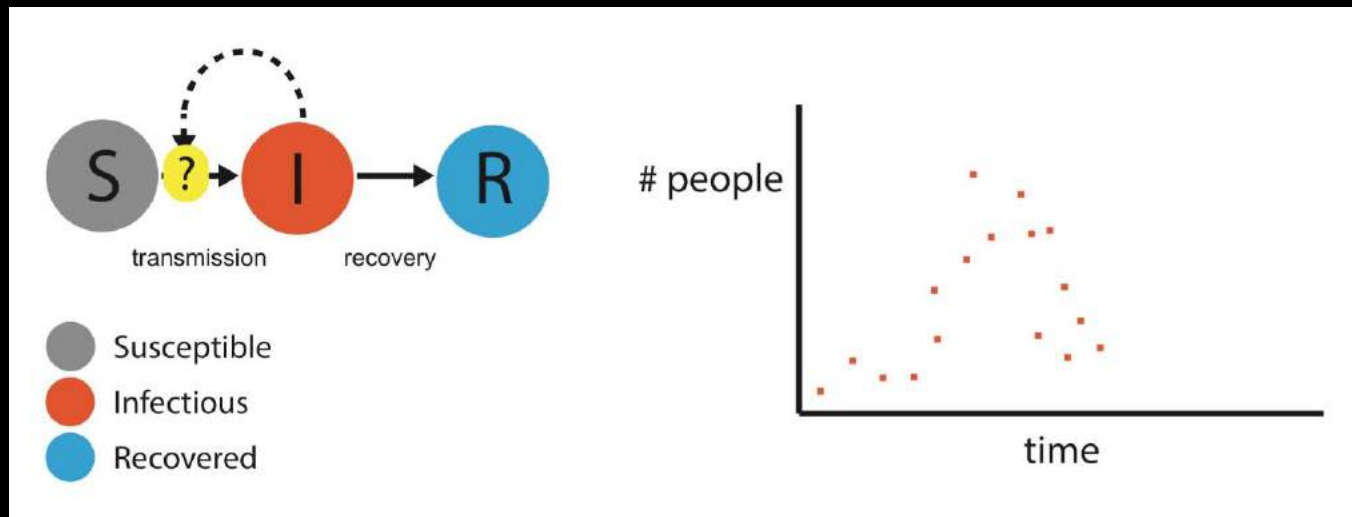
- Scale up from individual processes to population patterns
- “What if” scenarios not amenable to experimentation

What if we treated people and doubled the rate of recovery?



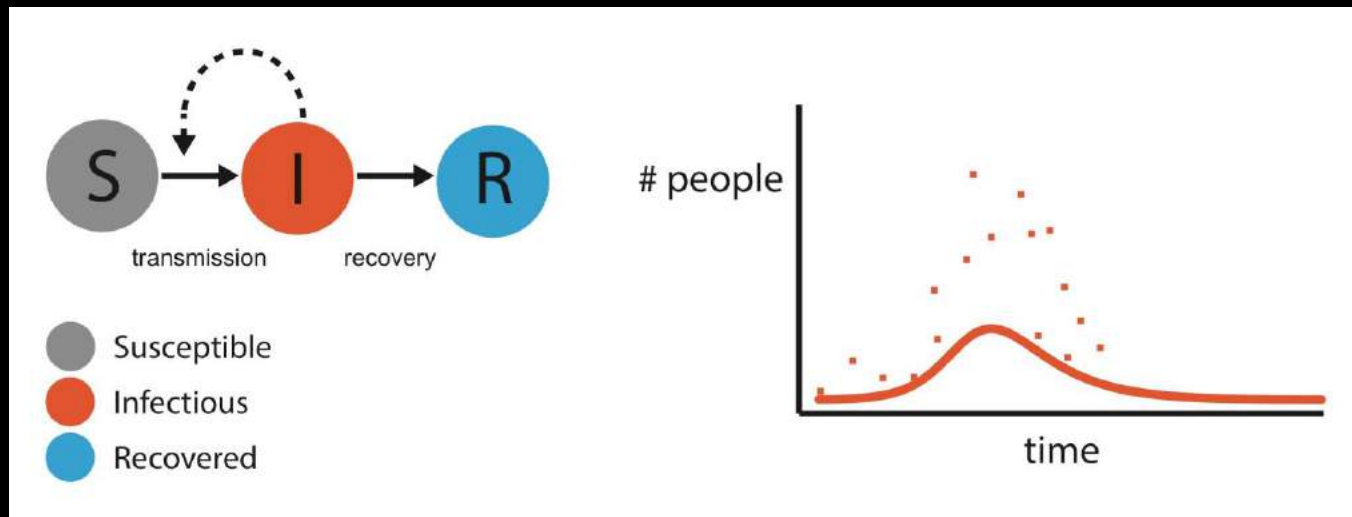
Mechanistic Epidemiology

- Scale up from individual processes to population patterns
- “What if” scenarios not amenable to experimentation
- Estimating parameters by fitting available data



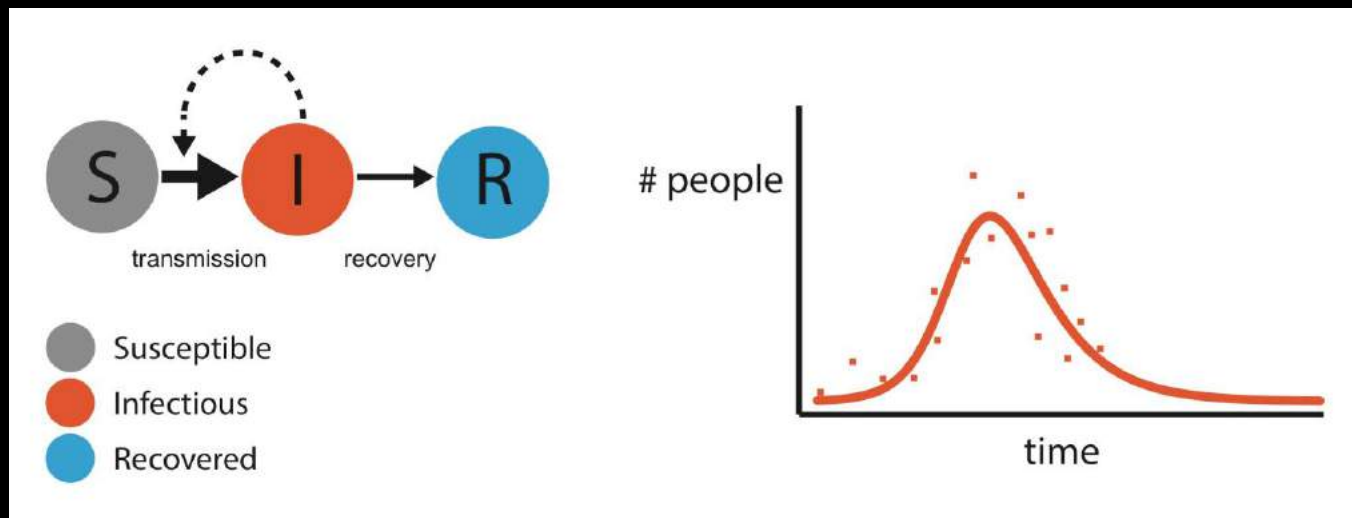
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Mechanistic Epidemiology

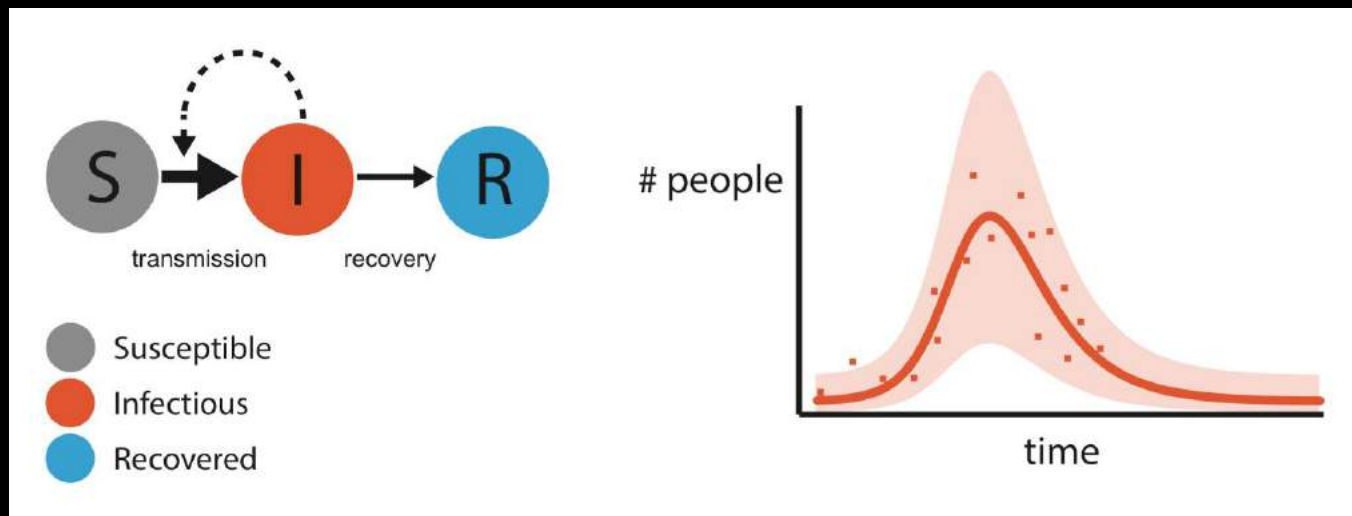
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Mechanistic Epidemiology

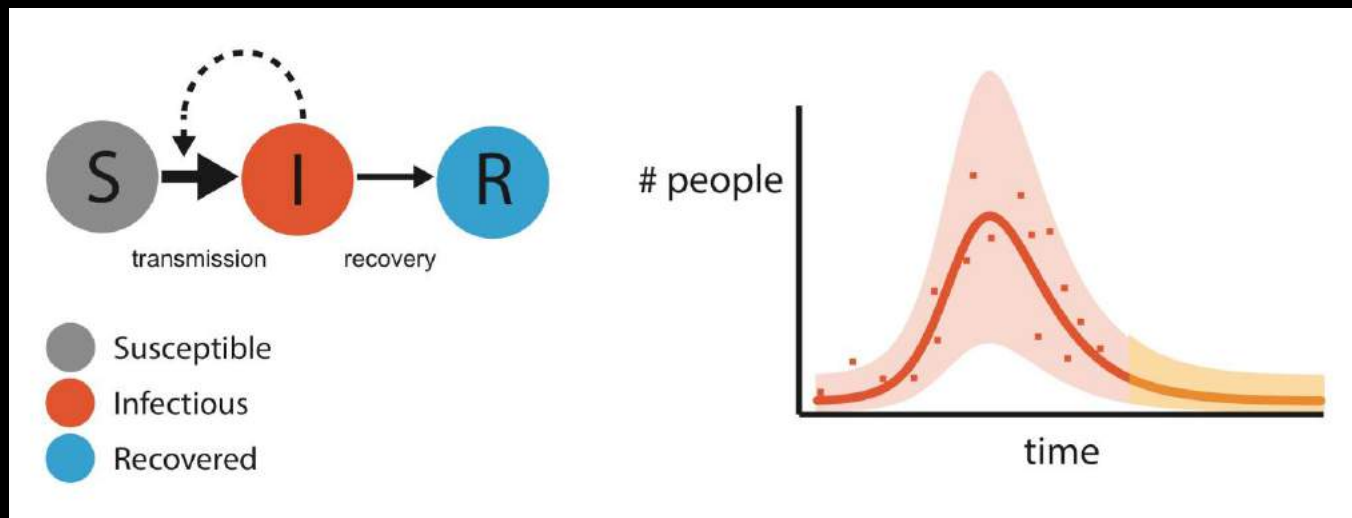
- Scale up from individual processes to population patterns
- “What if” scenarios not amenable to experimentation
- Estimating parameters by fitting available data

Estimate transmission rate or other model parameters
(with confidence intervals)



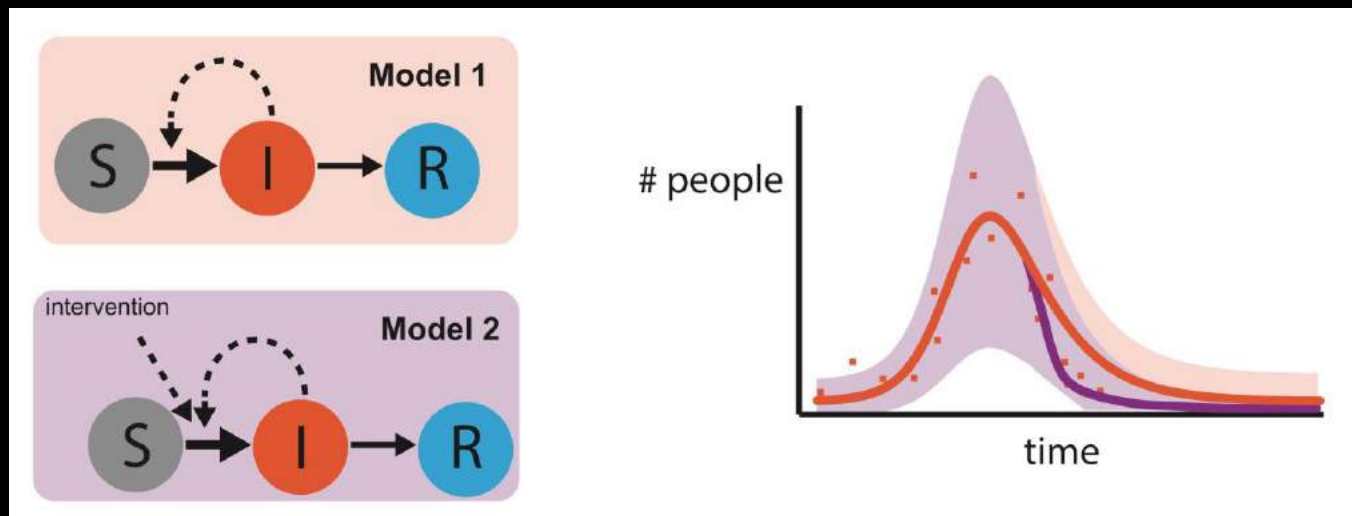
Mechanistic Epidemiology

- Scale up from individual processes to population patterns
- “What if” scenarios not amenable to experimentation
- Estimating parameters by fitting available data
- Prediction



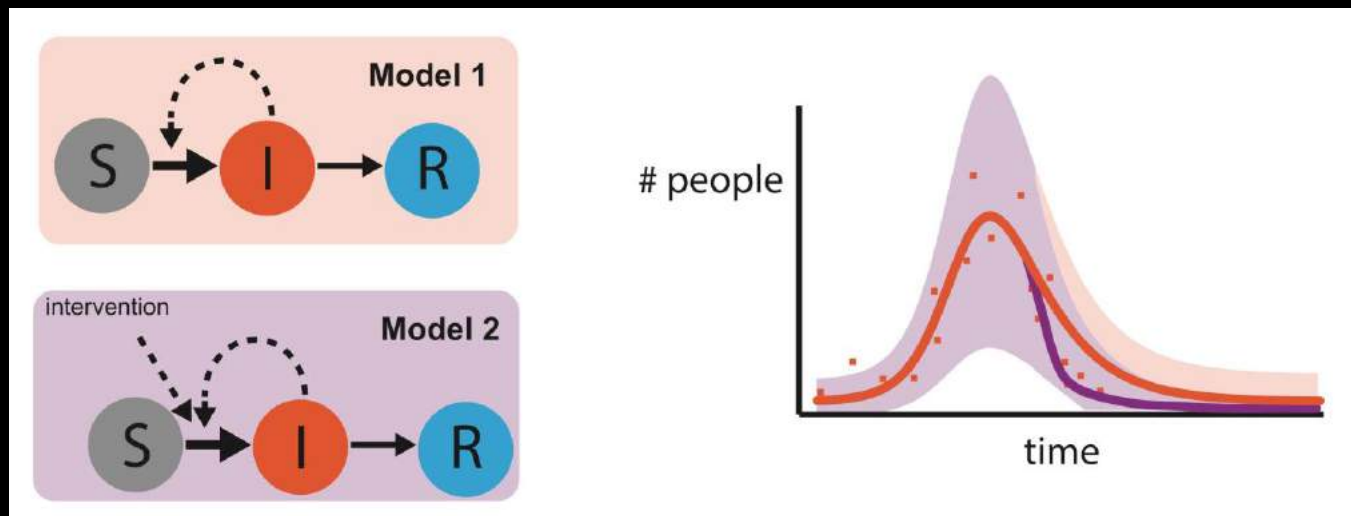
Mechanistic Epidemiology

- Scale up from individual processes to population patterns
- “What if” scenarios not amenable to experimentation
- Estimating parameters by fitting available data
- Prediction
- Model selection (choosing between alternative hypotheses)



Mechanistic Epidemiology

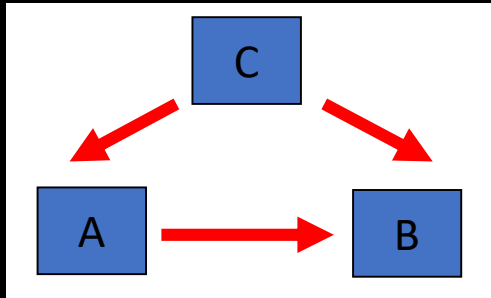
- Scale up from individual processes to population patterns
 - “What if” scenarios not amenable to experimentation
 - Estimating parameters by fitting available data
 - Prediction
 - Model selection
- data focus
emerged in
last 10 years



Classical Epidemiology

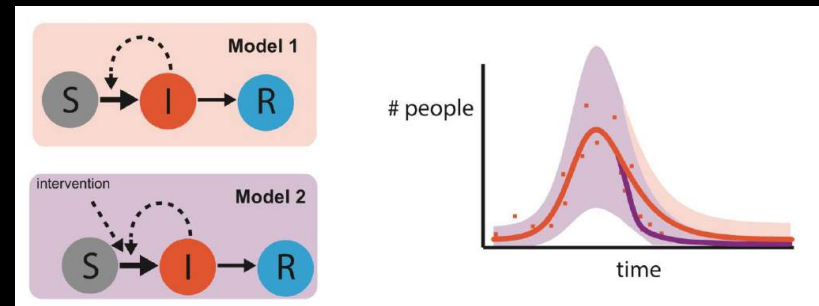
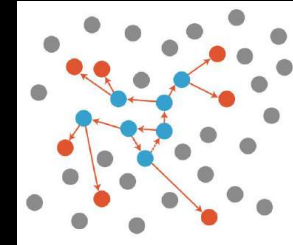
Data-Centric

Individual	Literate	HIV infected	Age	SES
1	0	0	5	high
2	0	0	8	high
3	0	0	7	low
4	0	1	16	low
5	1	1	35	low
6	1	0	28	high
7	1	1	18	low
8	1	1	45	high



Mechanistic Epidemiology

Process-Centric



An Integrative Approach

Mechanistically model both observation processes & underlying epidemiological processes

Vaccine Efficacy Trials

- Compare disease risk between
vaccinated & unvaccinated participants.
- If high risk people choose to be vaccinated, confounding
- Confounding avoided by **randomization**
- Randomized double-blinded placebo-controlled trials



Is randomization ethical?

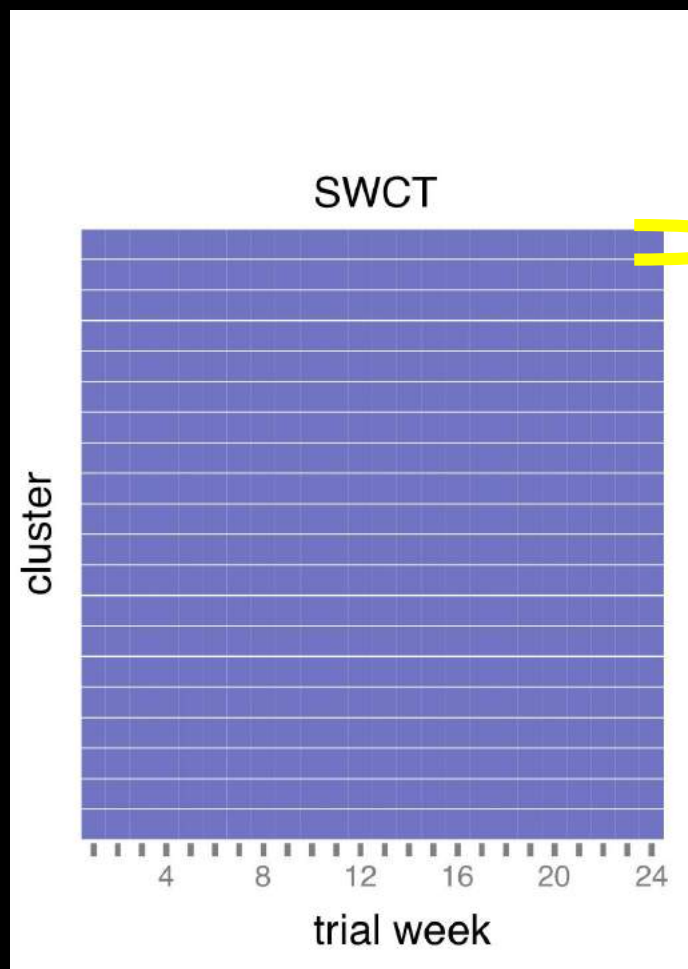
Equipoise

Uncertainty regarding whether
a participant is better off
receiving intervention or placebo.

Stepped Wedge Cluster Trial

- Evaluate vaccine when ethically problematic to withhold intervention
- Vaccinate everyone *as fast as possible*, by groups, in random group-order
- Compare infection risk between
vaccinated & not-yet-vaccinated individuals
- Randomized group-order avoids confounding

Stepped Wedge Cluster Trial

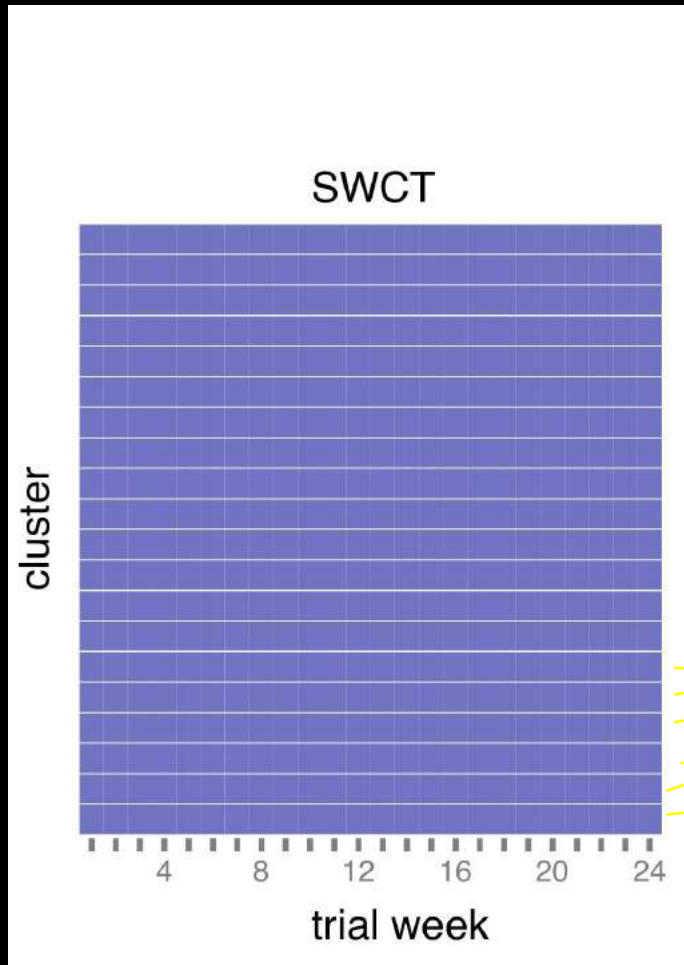


Cluster of 300 frontline caregivers (HCW+)

x20

Observed for 24 weeks (6 months)

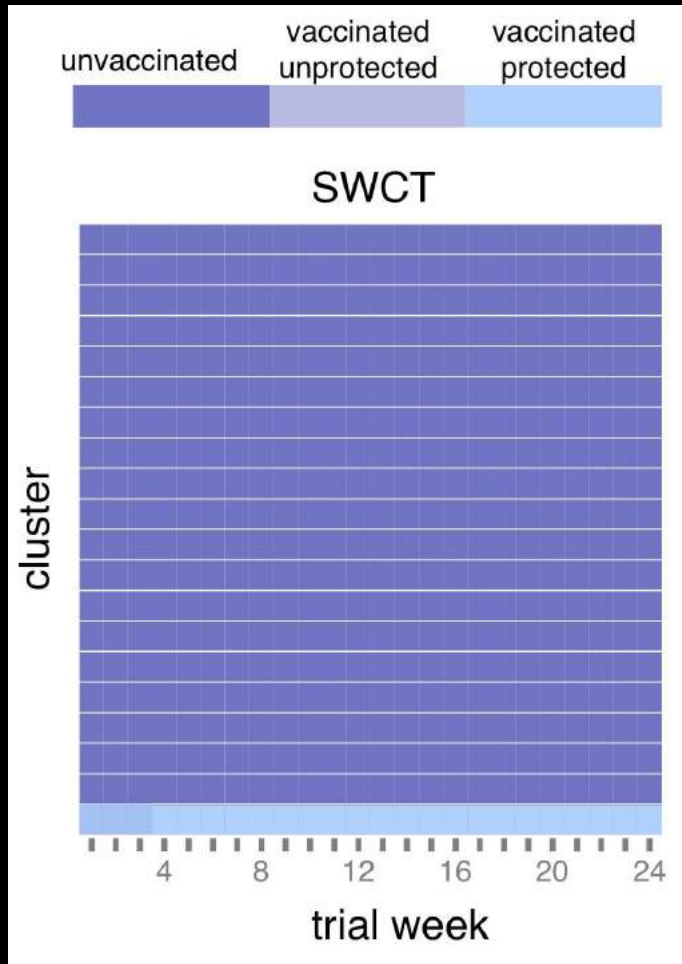
Stepped Wedge Cluster Trial



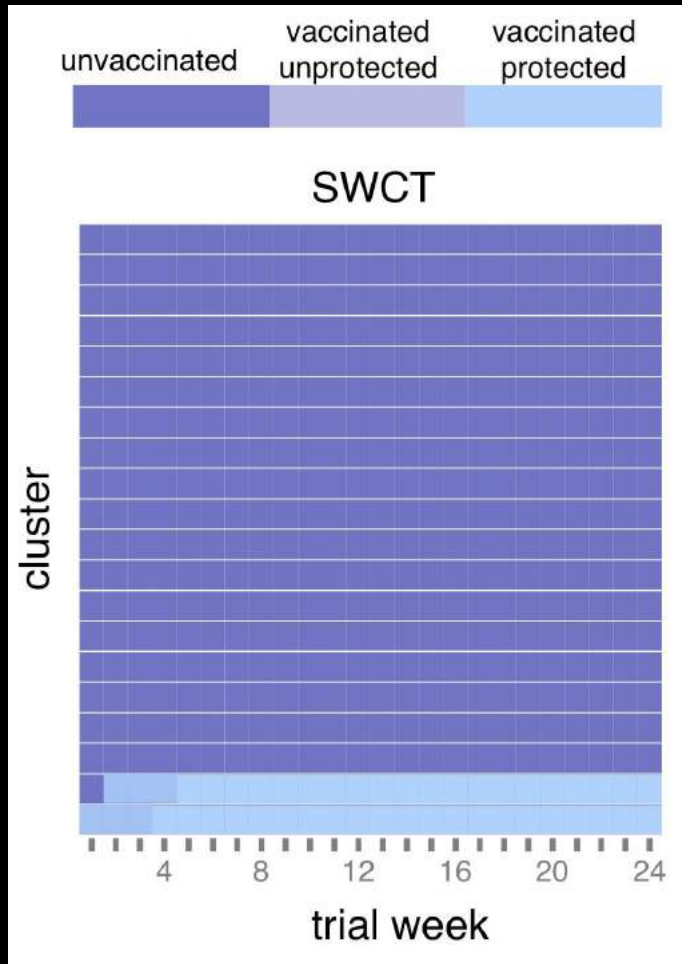
Clusters from geographically distinct areas



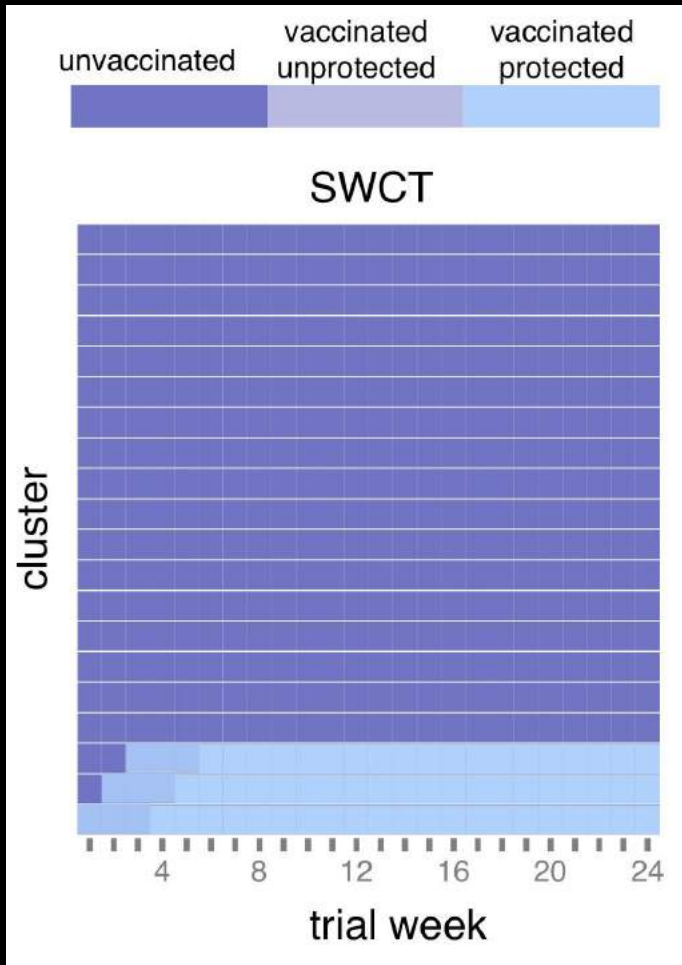
Stepped Wedge Cluster Trial



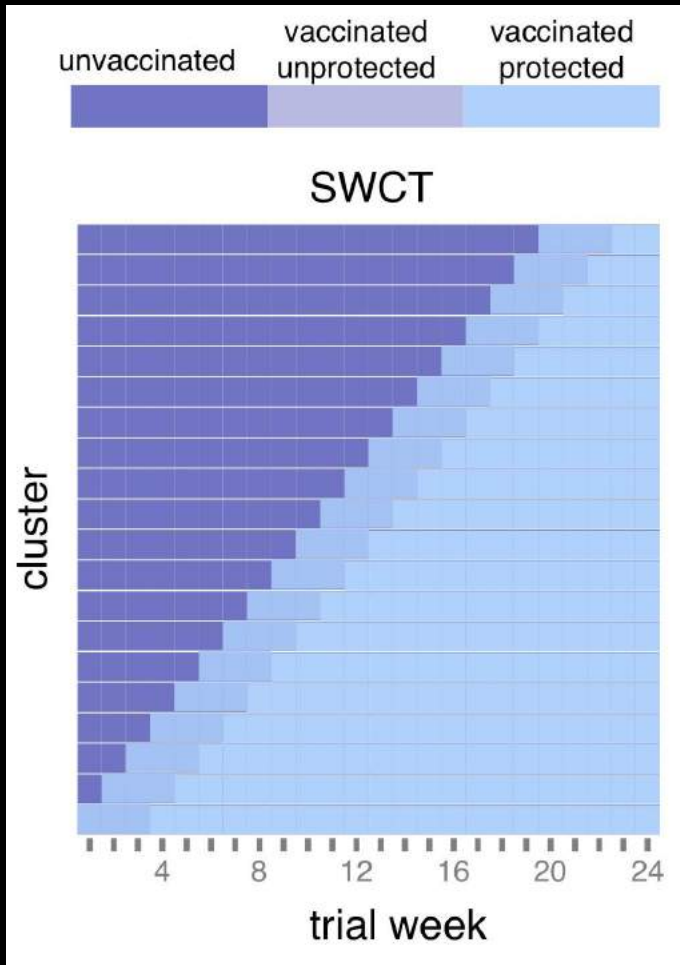
Stepped Wedge Cluster Trial



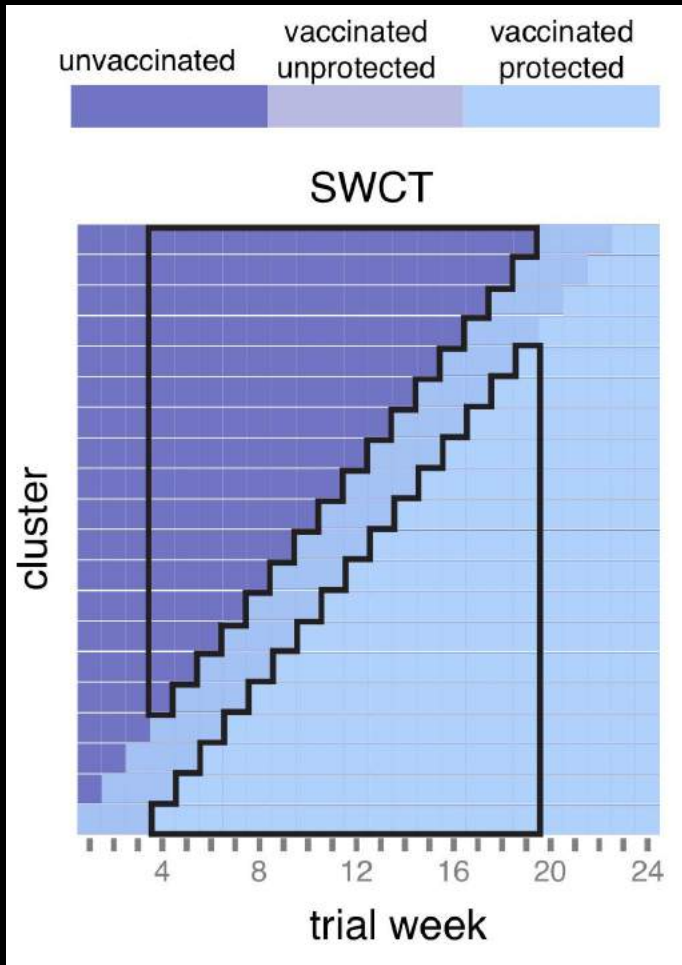
Stepped Wedge Cluster Trial



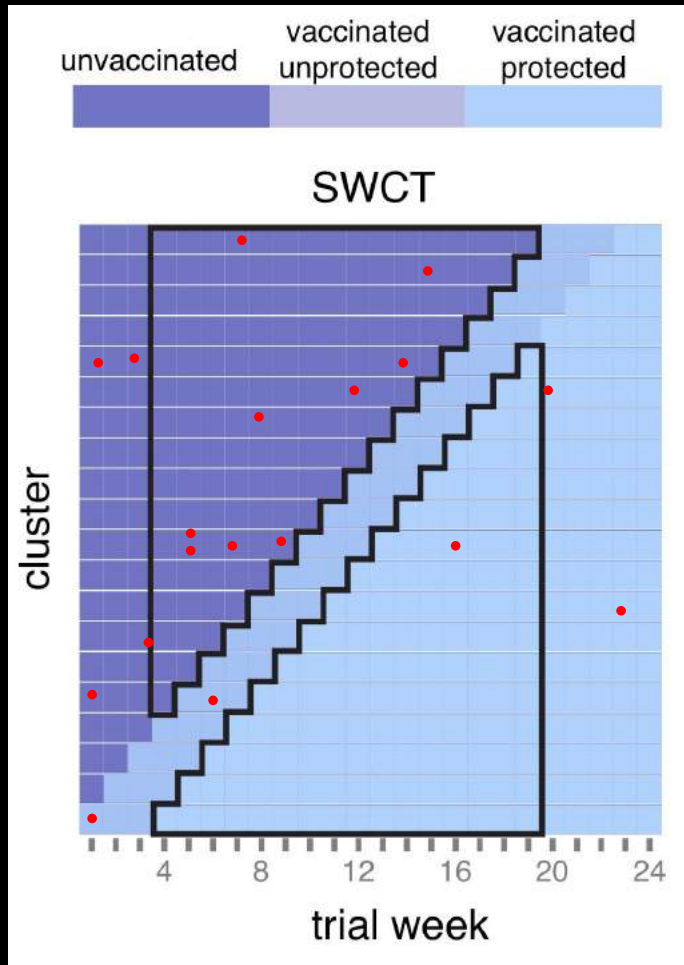
Stepped Wedge Cluster Trial



Stepped Wedge Cluster Trial

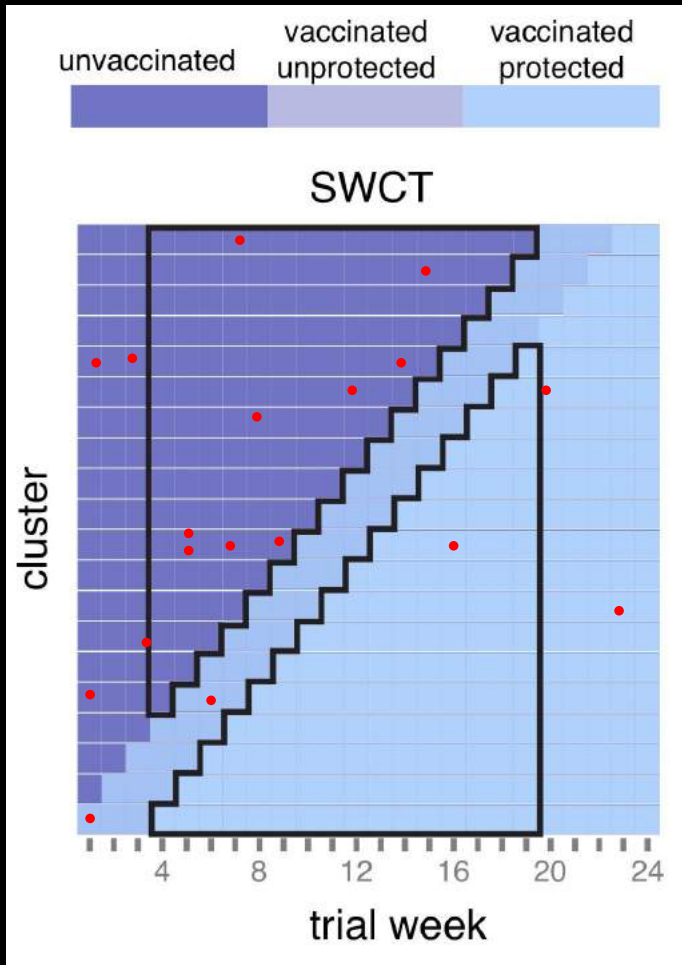


Stepped Wedge Cluster Trial



● infected participant

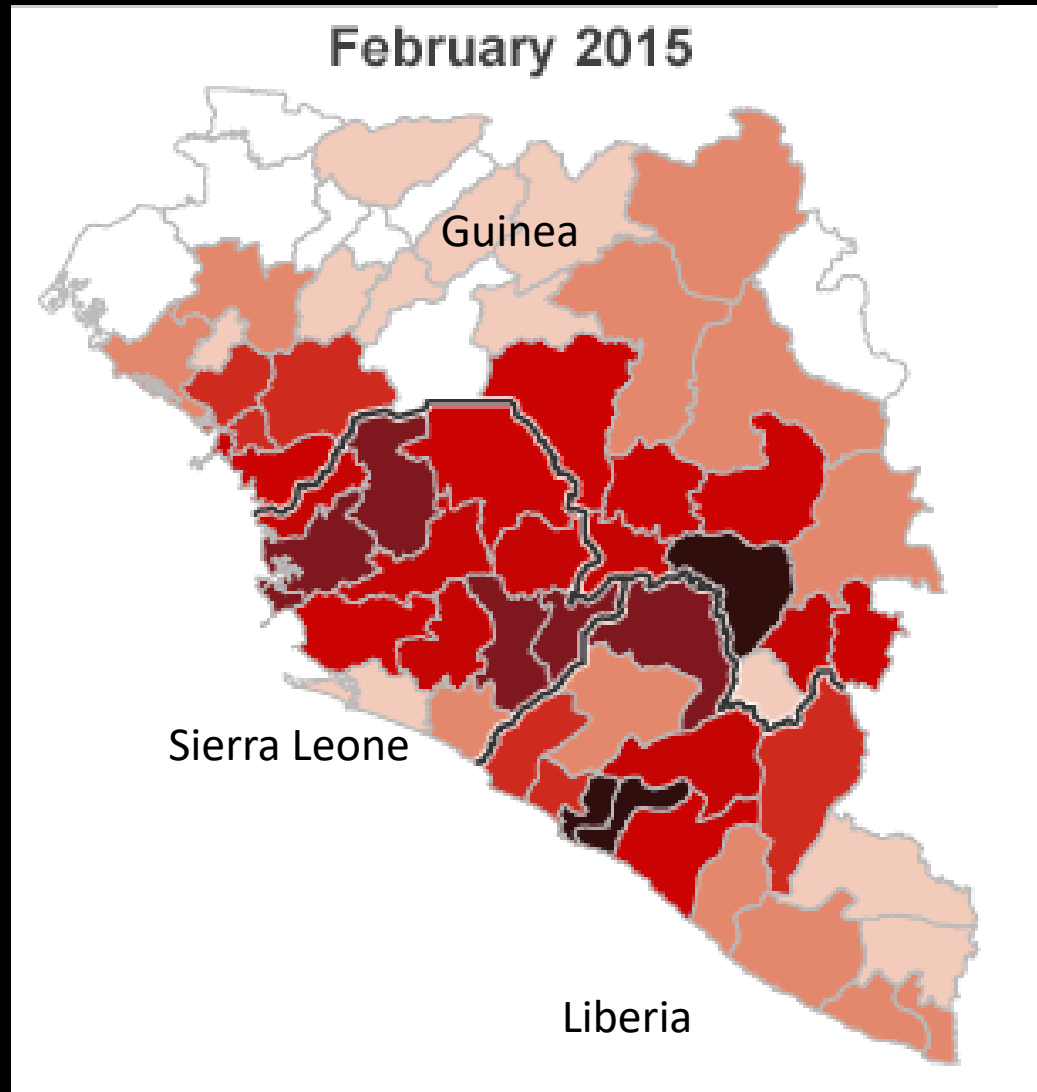
Stepped Wedge Cluster Trial



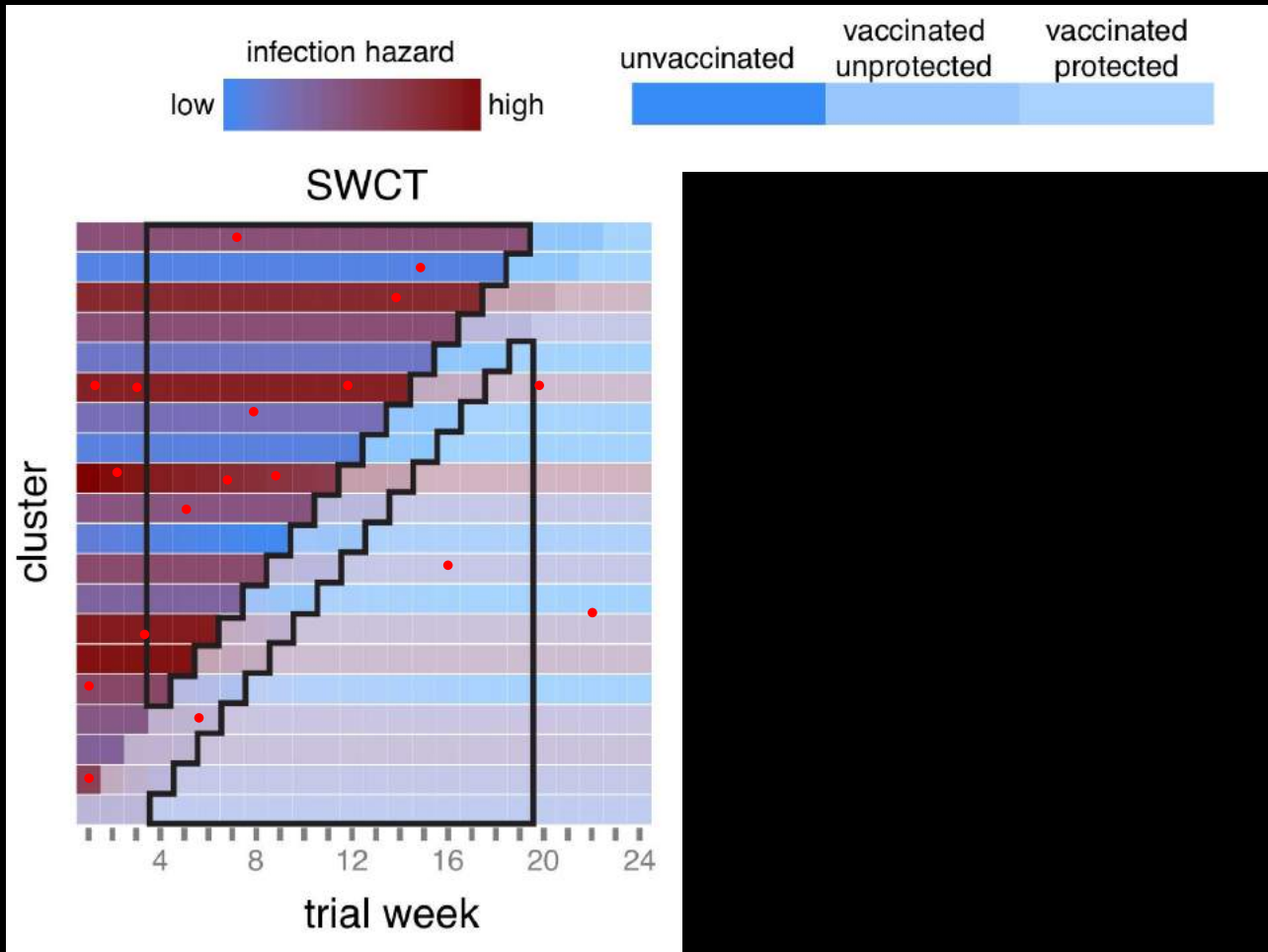
Nov 2014

Jan 2014

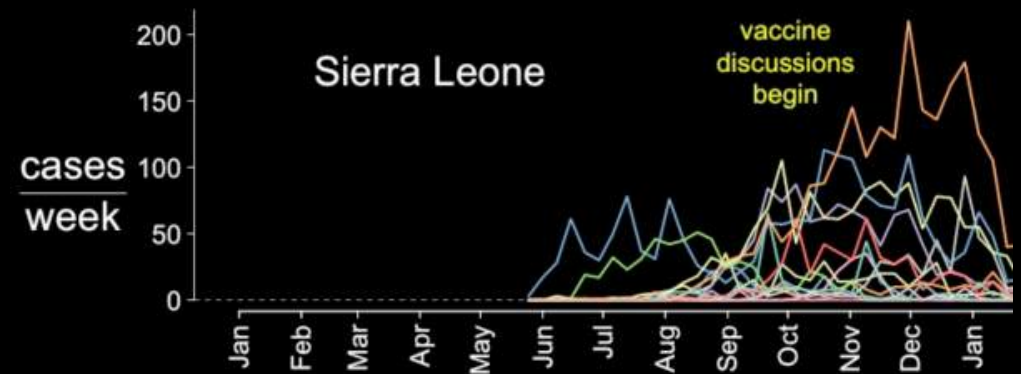
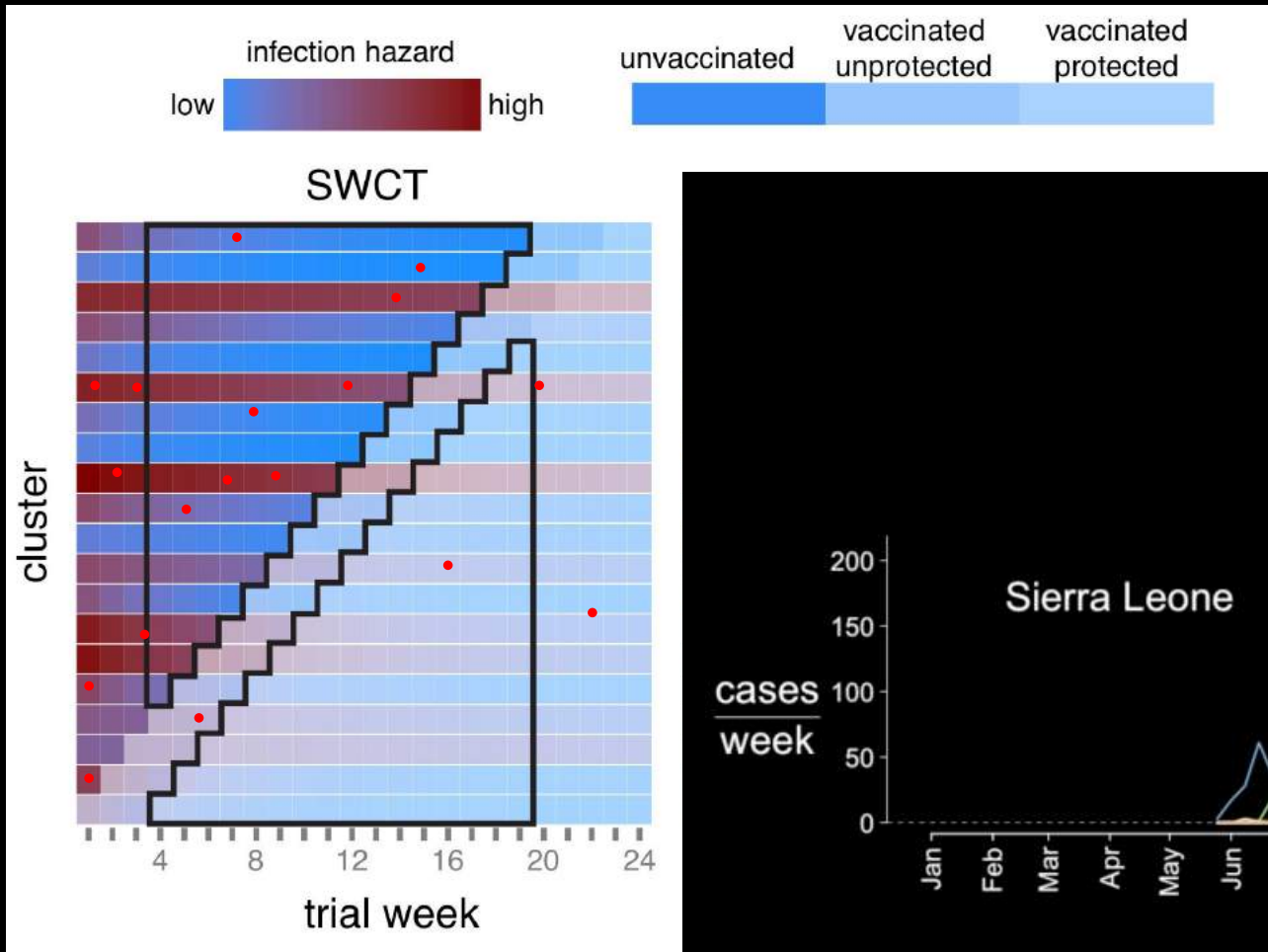
Regional Variation in Ebola Cases



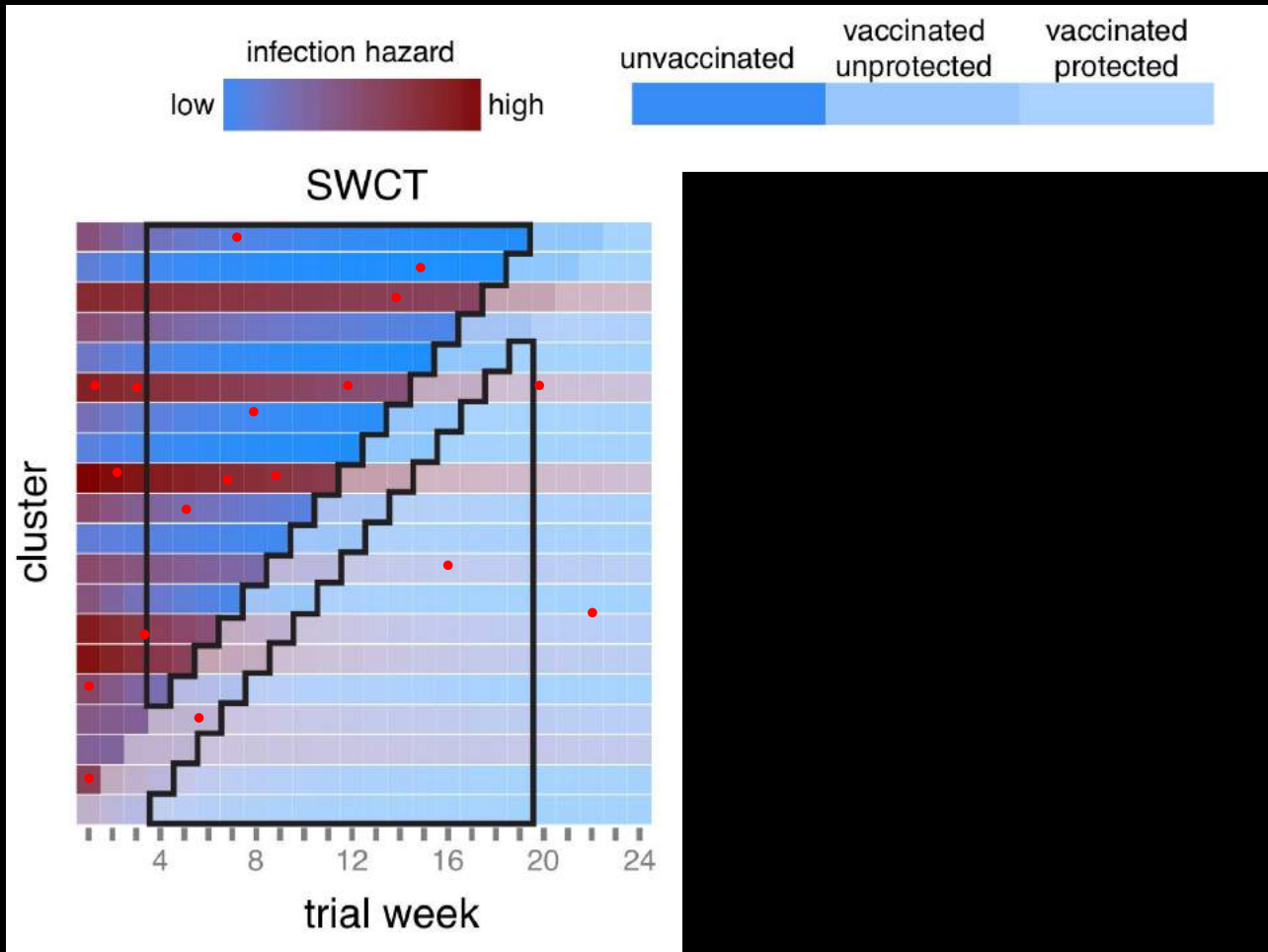
Stepped Wedge Cluster Trial



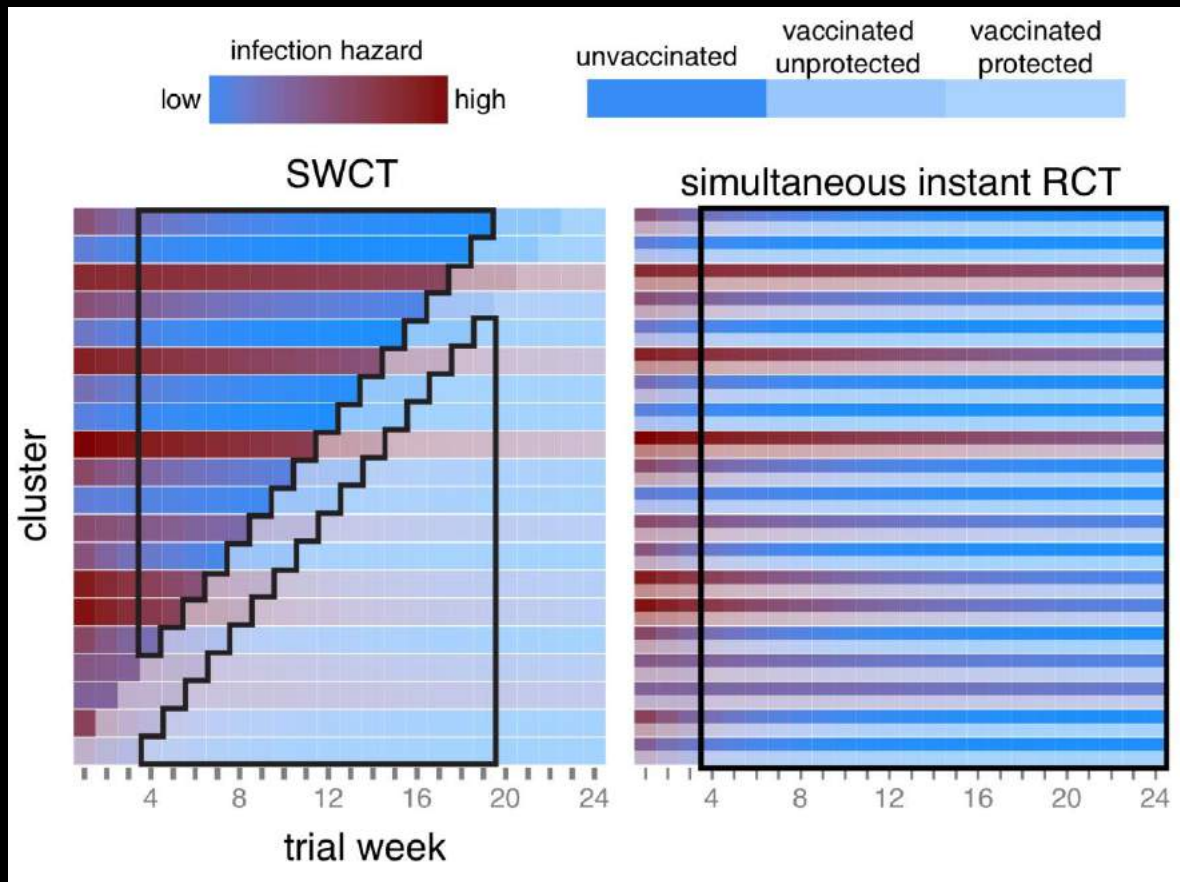
Stepped Wedge Cluster Trial



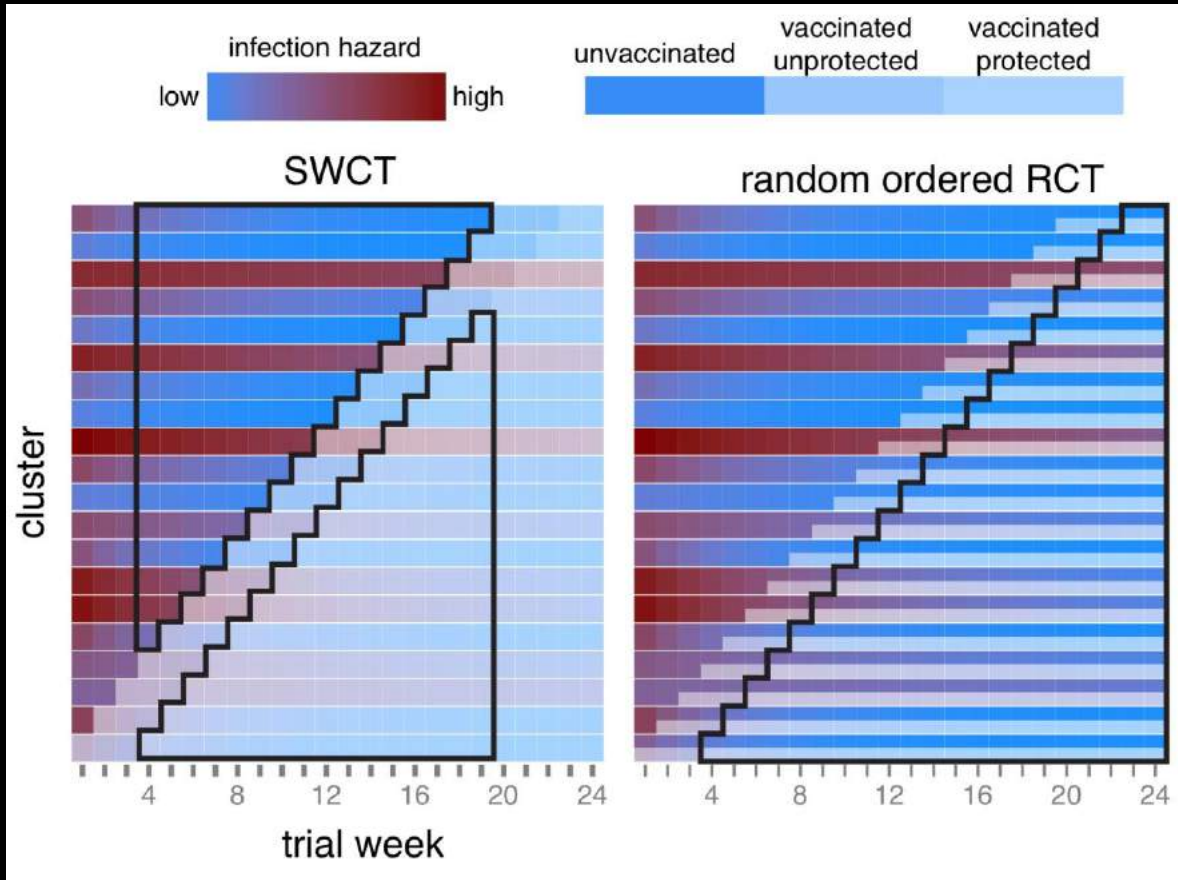
Stepped Wedge Cluster Trial



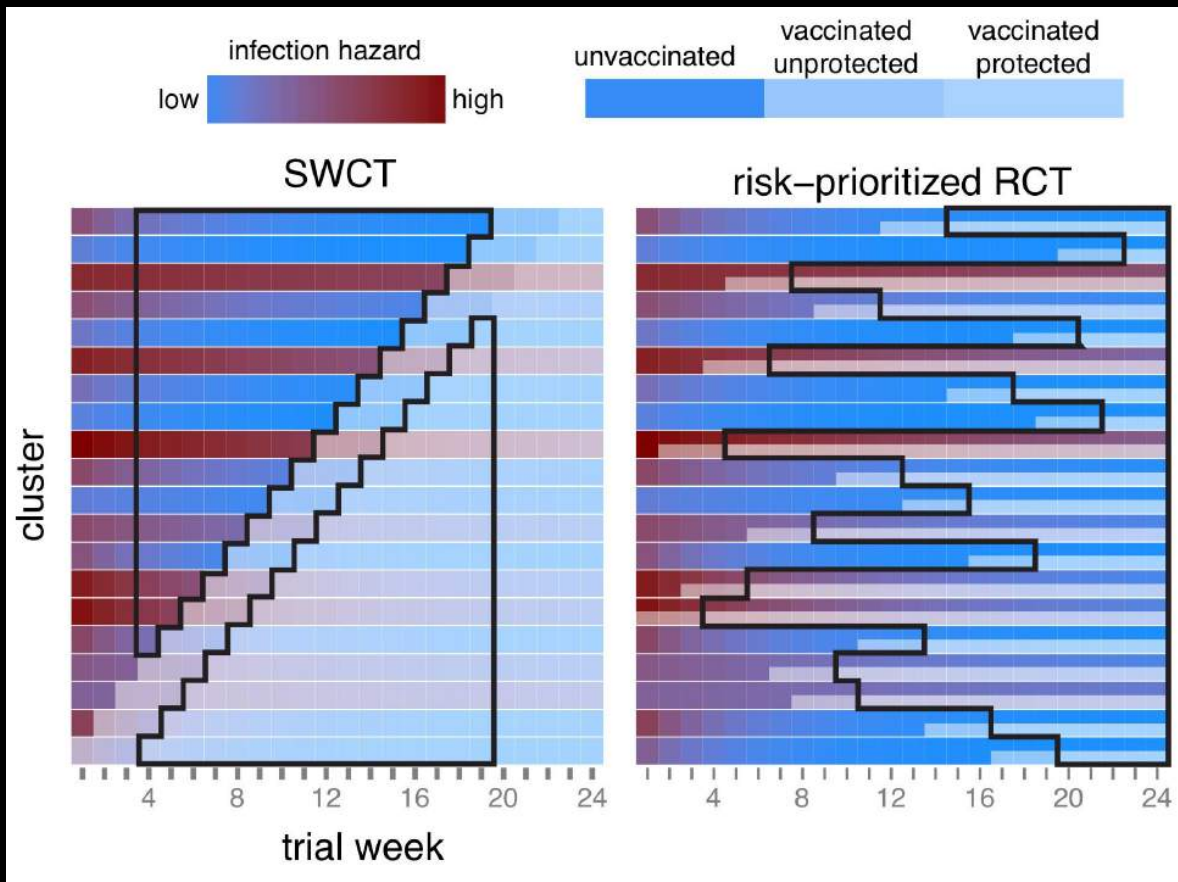
Other Options



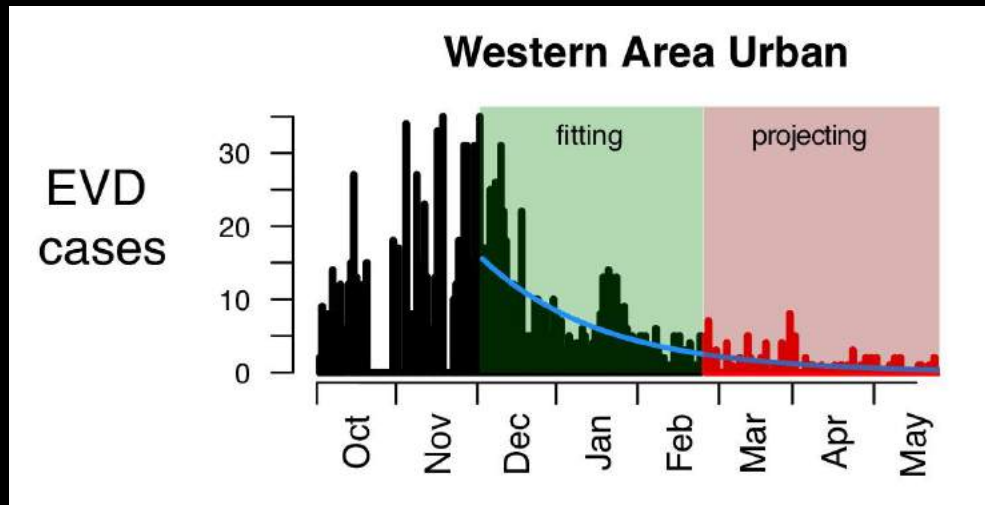
Other Options



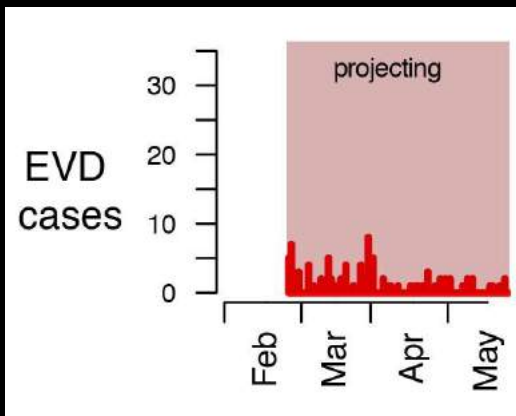
Other Options



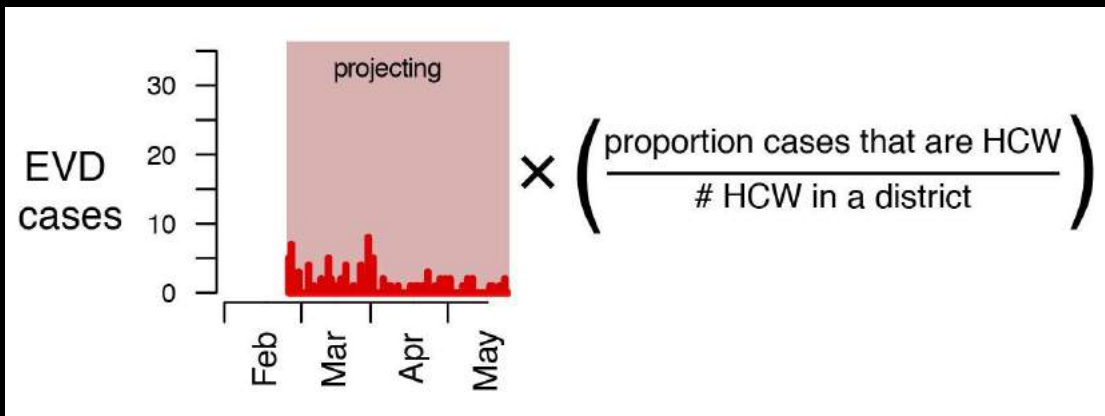
Project Declining Epidemics



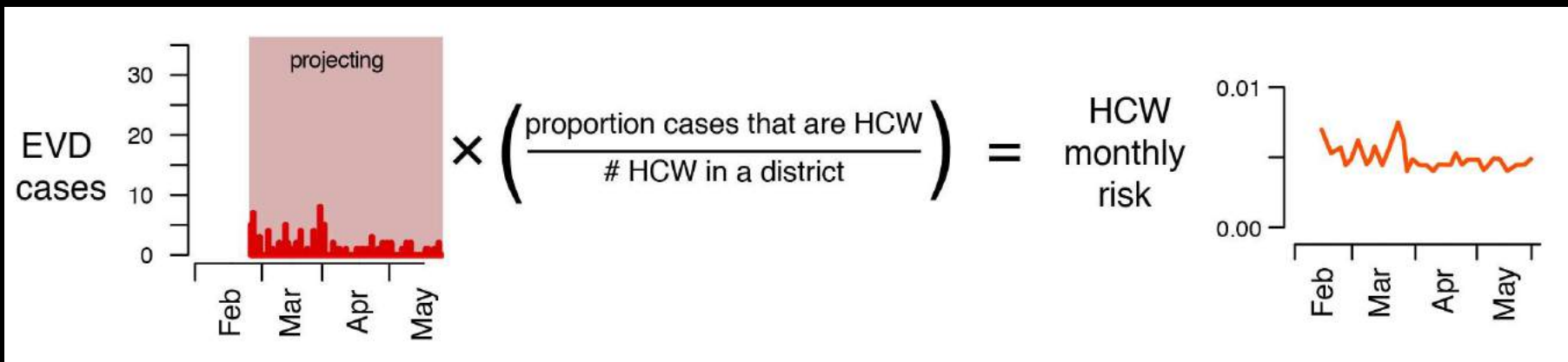
Project Declining Epidemics



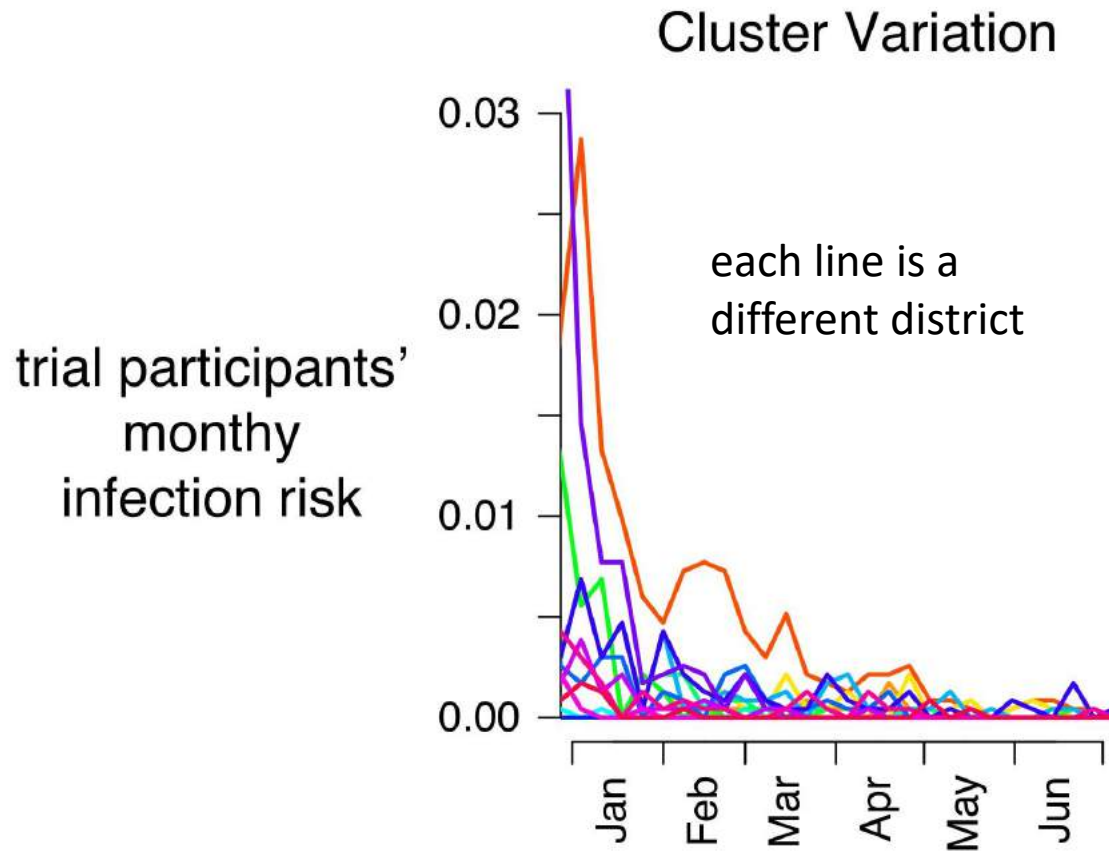
Project Declining Epidemics



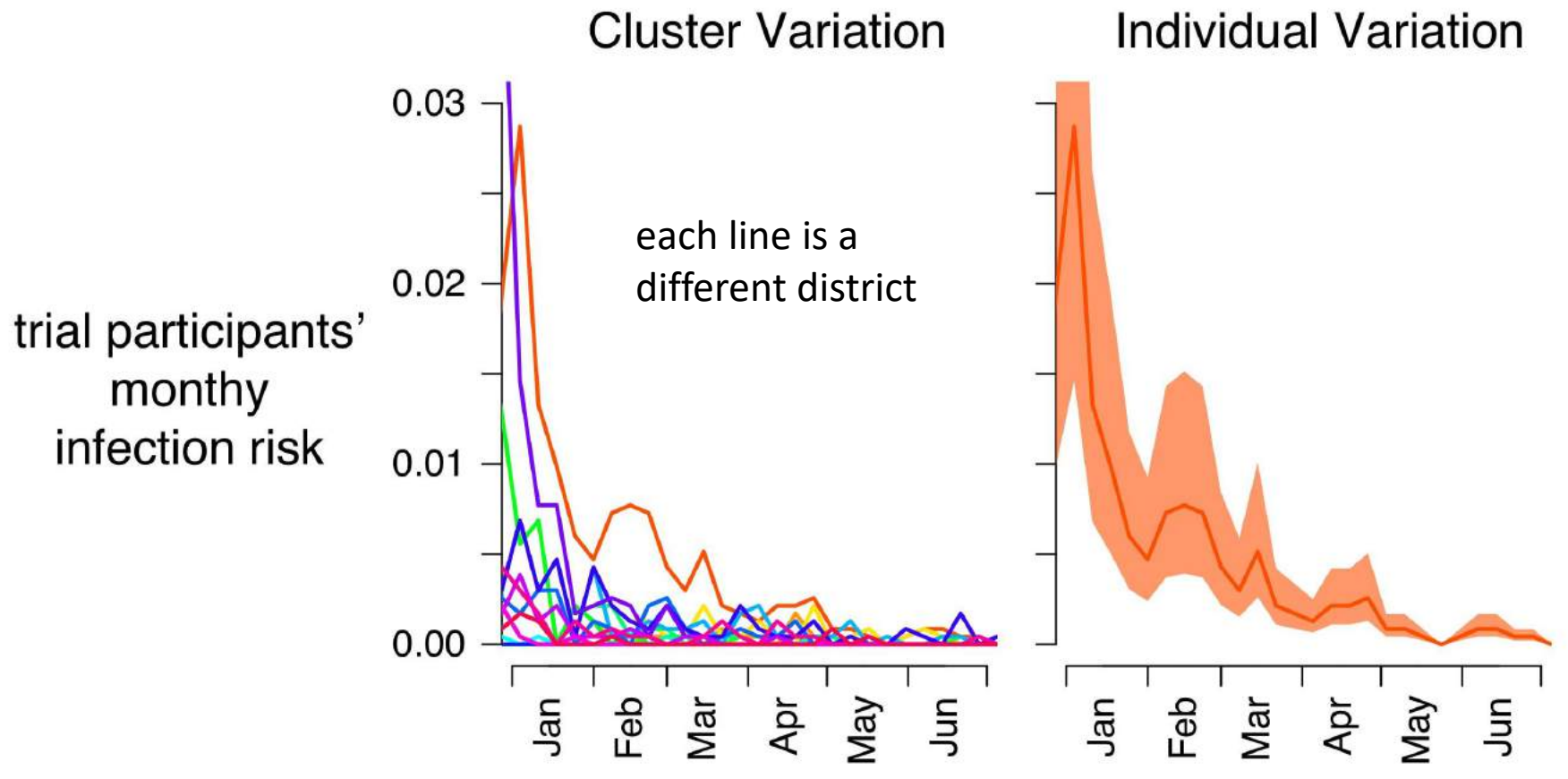
Project Declining Epidemics



Modeling Ebola Risk



Modeling Ebola Risk



Evaluating Trial Designs

1. Fit epidemic declines with decay model.

1. Simulate stochastic epidemic projections
2. Simulate trial population with risk determined by projections.
3. Simulate vaccine trial design.
4. Analyze data.

× 2000 for each scenario

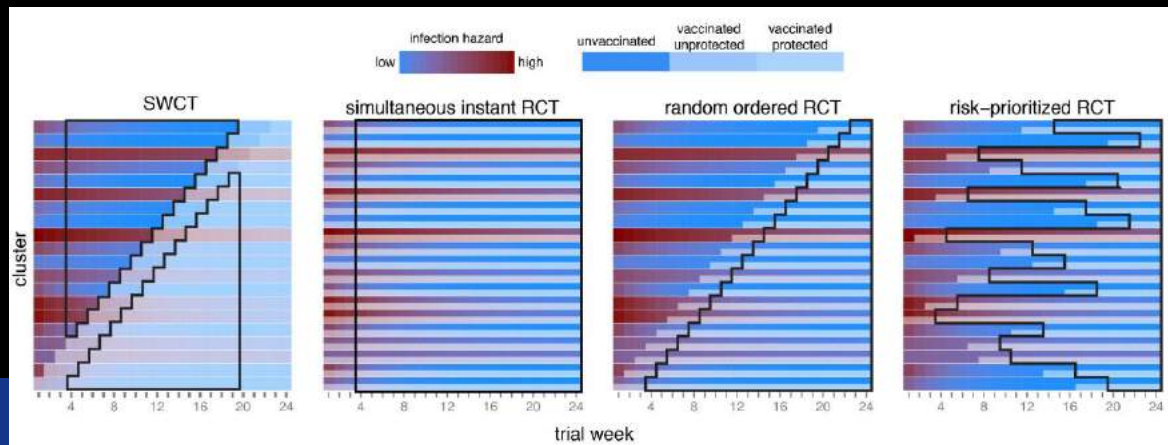
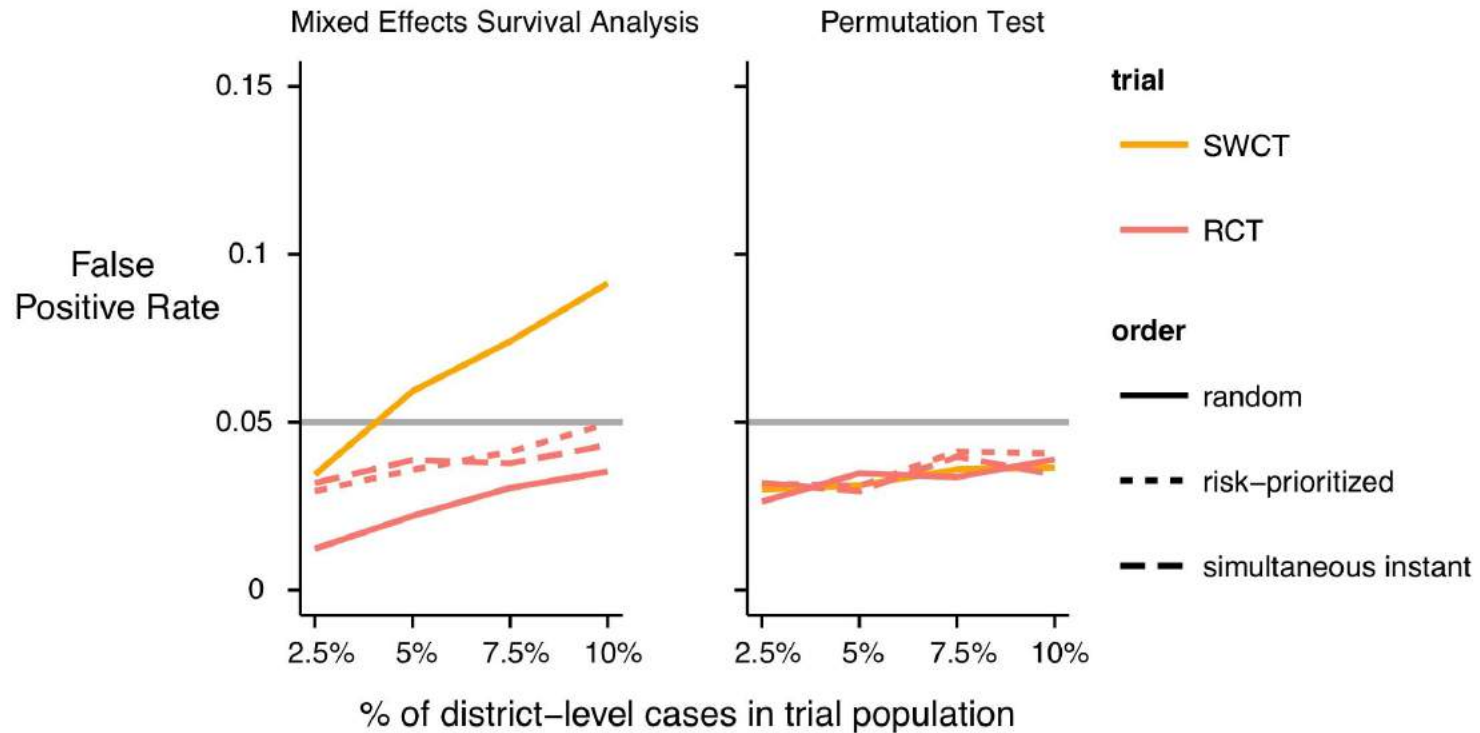
False Positive Rate

If vaccine is *not* efficacious, % times we conclude it is efficacious

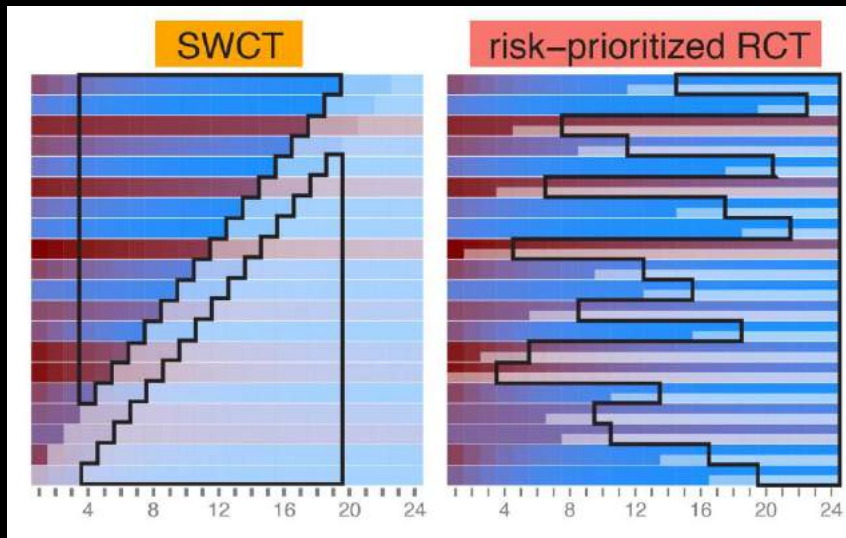
Statistical Power

If vaccine is efficacious, % times we conclude it is efficacious

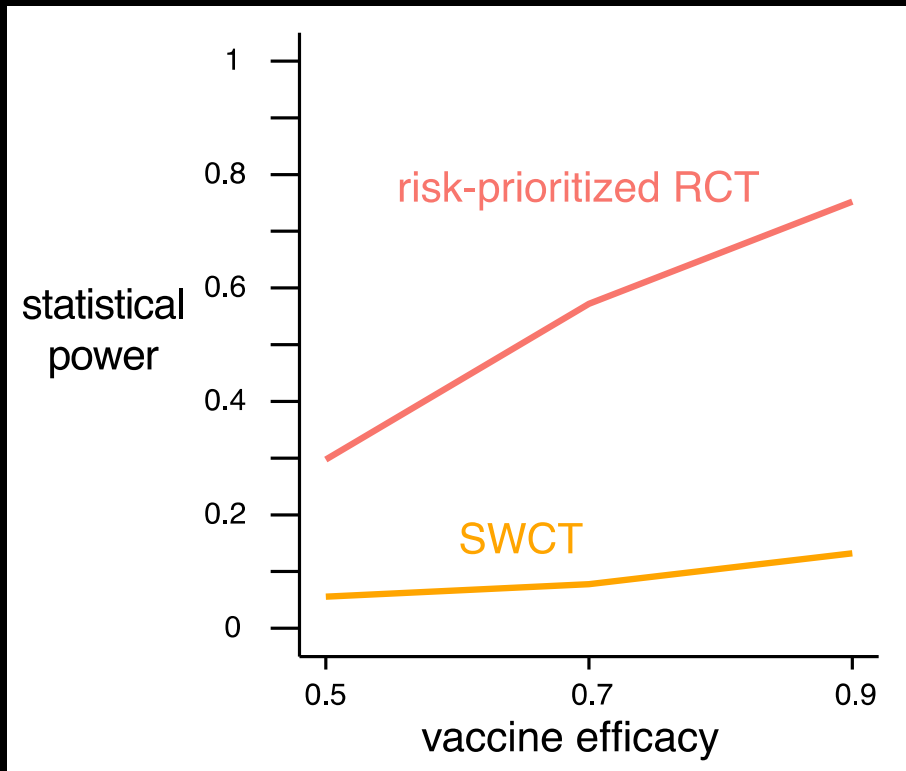
False Positive Rates



Statistical Power



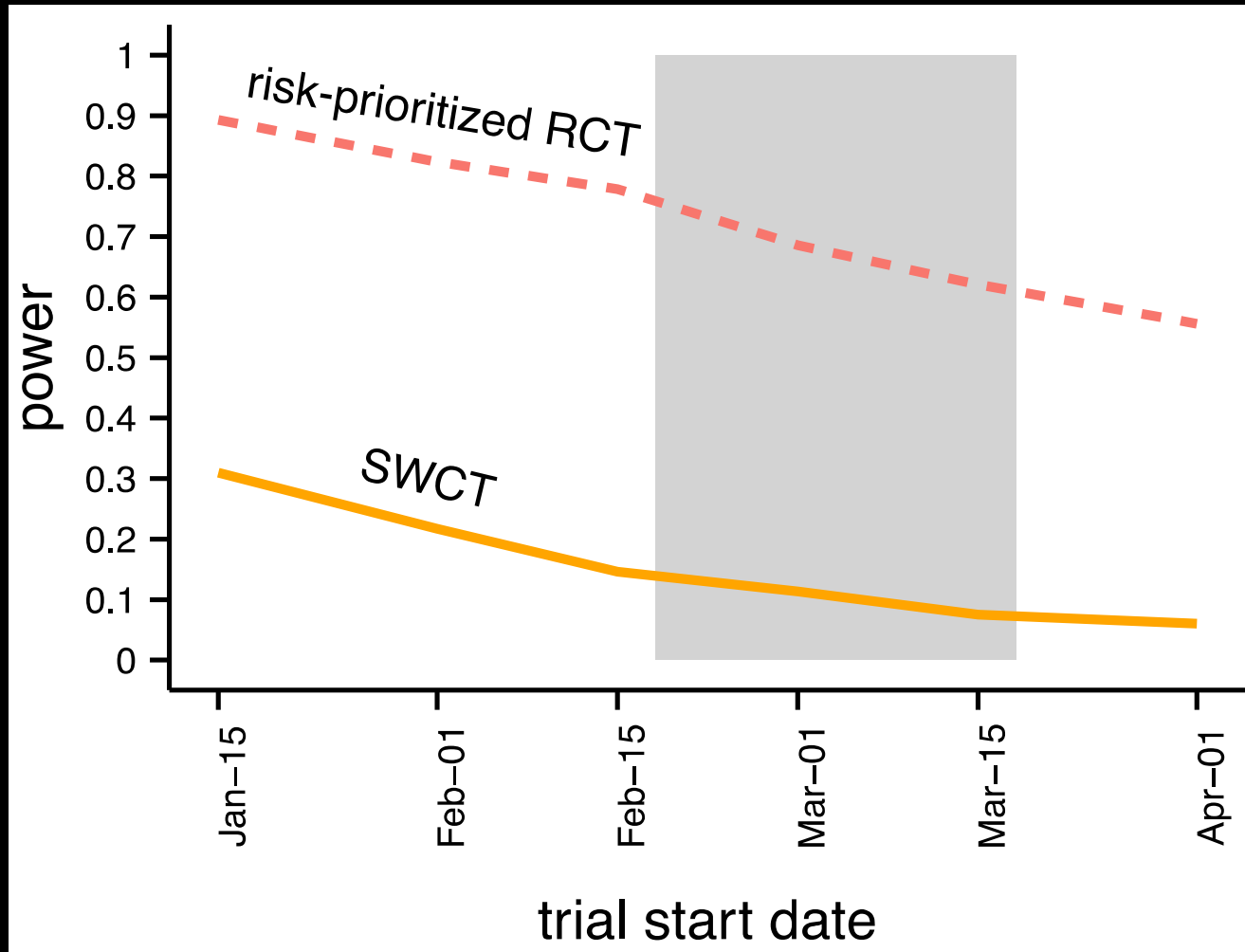
Risk-prioritized RCT far more statistically powerful in this context.



SWCT has < 15% power of detecting an efficacious vaccine.

Very inefficient for spatiotemporally variable settings

Speed is a Priority!

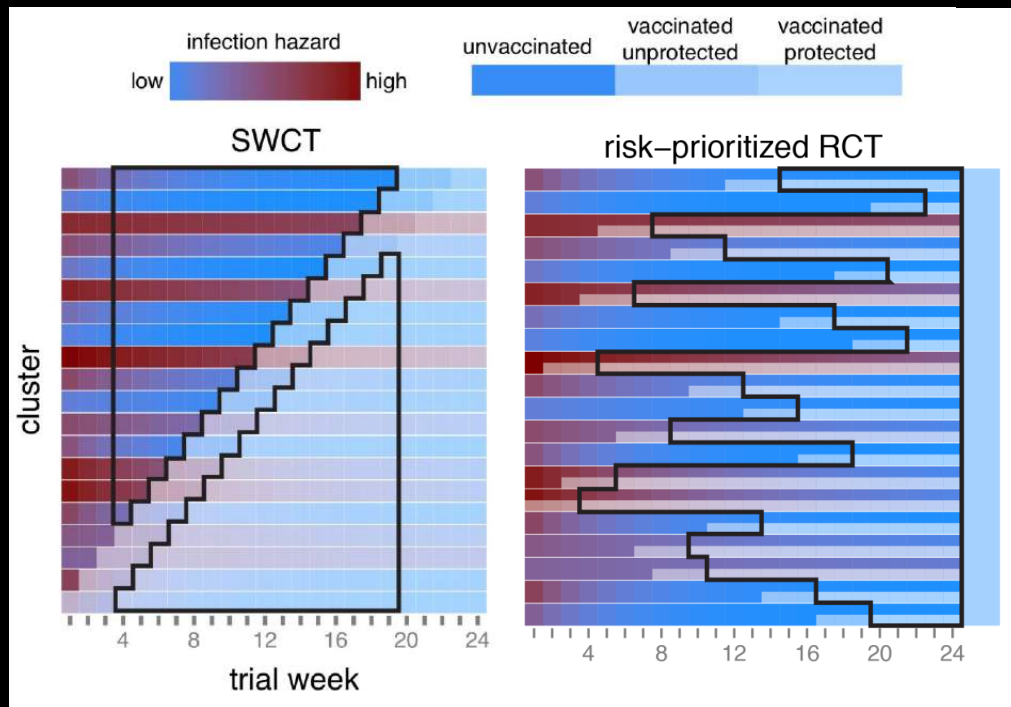


Bellan et al. 2015. *Lancet ID*.

What about ethics?

Avoids Equipoise Concern

1. No control groups
2. Vaccinate everyone *as fast as possible*
(no prioritization of information over outcomes)



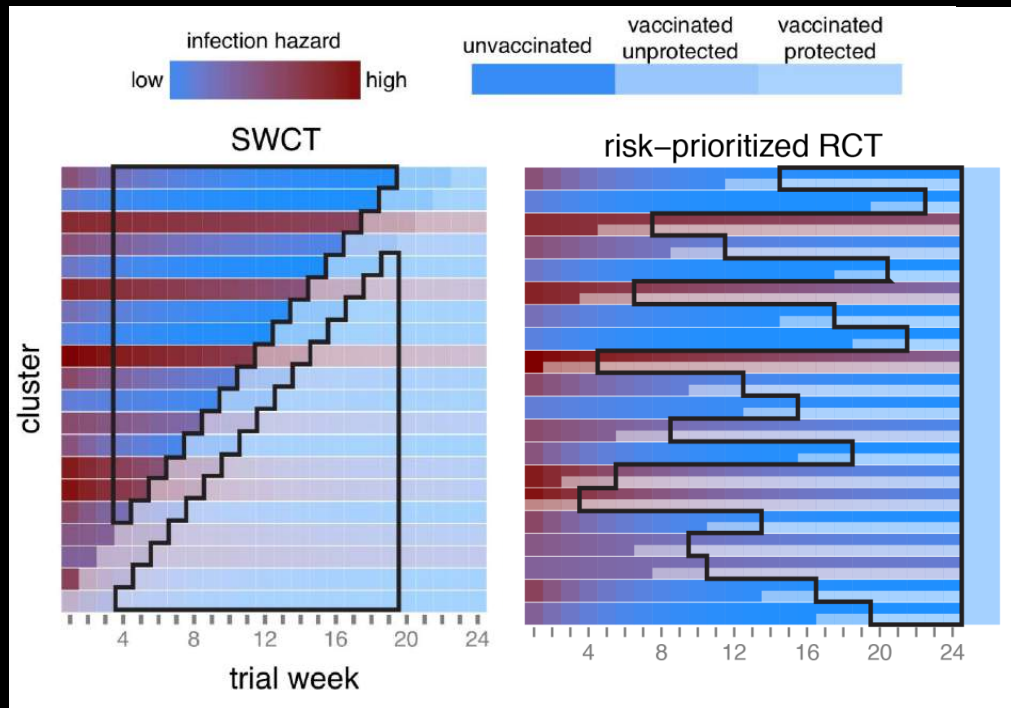
But high risk people
should be vaccinated
first...

Bellan et al. 2015. *Lancet ID*.

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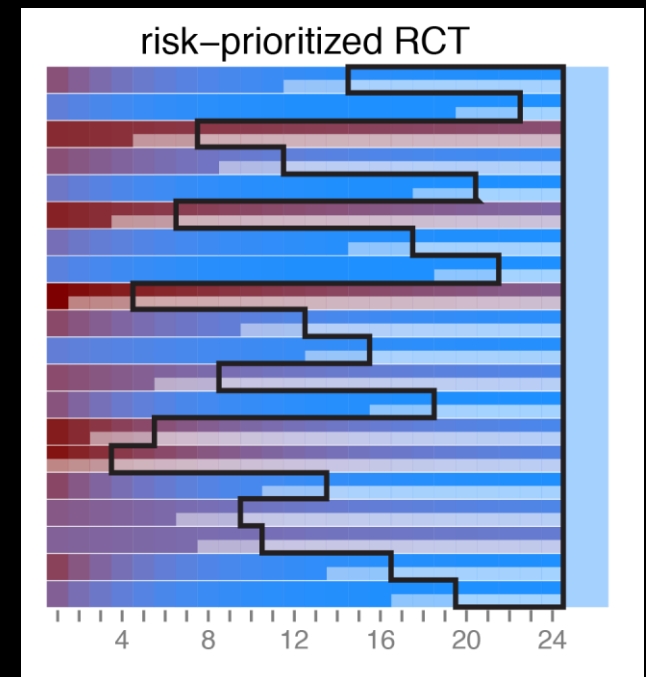


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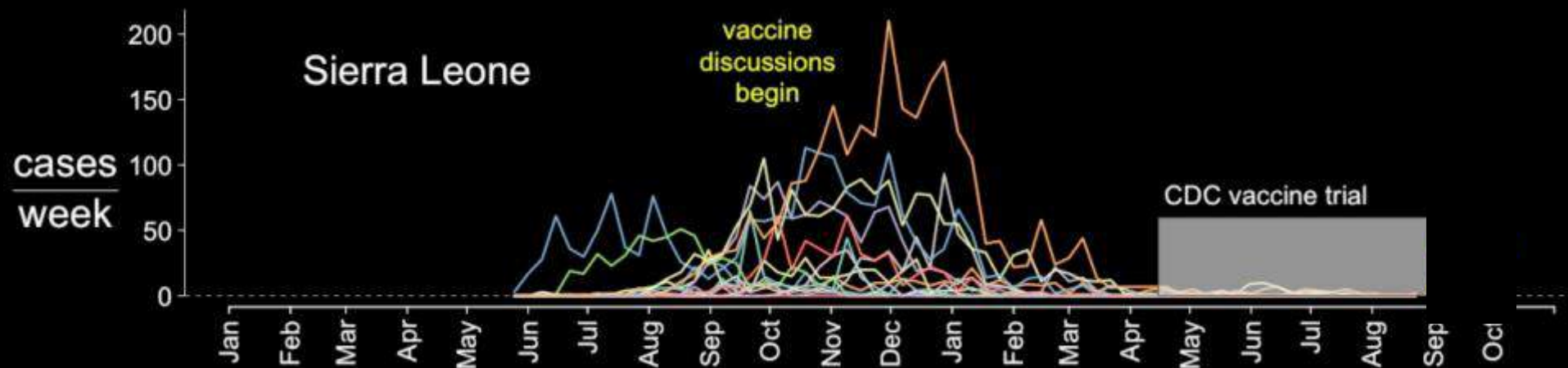
Bellan et al. 2015. *Lancet ID*.



Informed by our analysis,
CDC did a risk-prioritized RCT.



Vaccinated everyone at the end.



Computational Resources

- 600,000 simulated trials (2K for 300 scenarios)
- 480 million statistical models fit
- 2 days on TX Advanced Computing Cluster
- Total analysis done in 3 weeks

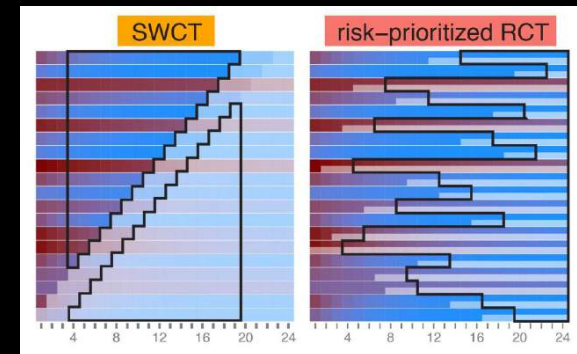
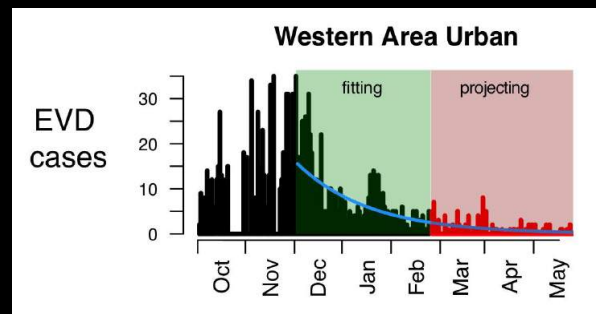
Interactions with CDC

- Dialogue/collaboration with CDC Modelers (Lopman, Gambhir)
- Results discussed in CDC Vaccine Team Meetings
- CDC already leaning towards phased-RCT due to adaptability in declining epidemic context
- Results were influential in helping CDC think through new design
- Ongoing CDC STRIVE began April 14th

Integrative Approach

process-centric

data-centric



Model Taxonomy

CONTINUOUS TREATMENT OF INDIVIDUALS
(averages, proportions, or population densities)

DISCRETE TREATMENT OF INDIVIDUALS

DETERMINISTIC

CONTINUOUS TIME

DISCRETE TIME

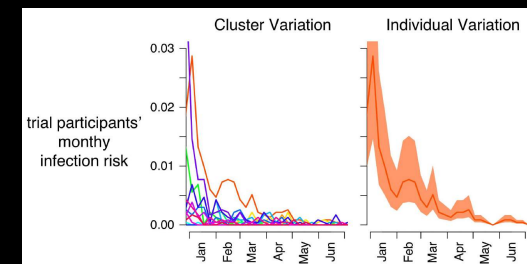
STOCHASTIC

CONTINUOUS TIME

DISCRETE TIME

CONTINUOUS TIME

DISCRETE TIME



Philosophy of Modeling & Trial Design

Analytical Power
Analyses

Classical Power
Simulations

Trials superimposed over
transmission modeling

Risk-Model Fitted
to Epi Data

Compartmental
Models

Individual-Based
Models

Abstract

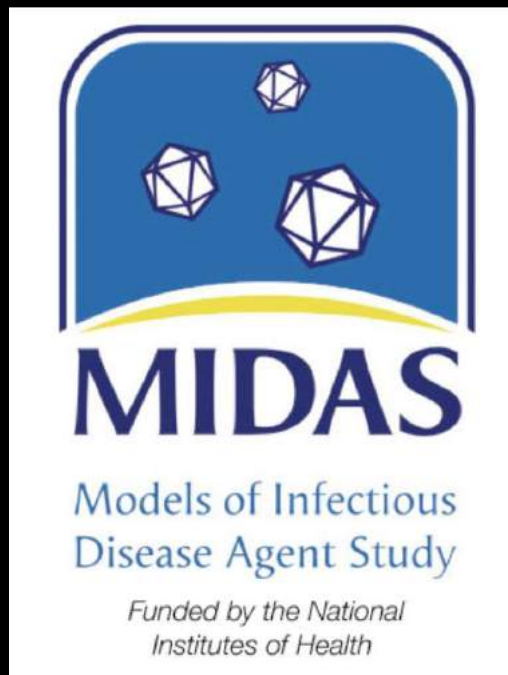
Concrete

Summary

- Trial design requires thinking both from data- & process- centric perspectives
- Simulation can reveal weaknesses in designs
- Intuitive arguments for specific designs may be wrong → SIMULATE!

Acknowledgements

- Lauren Ancel Meyers, Jonathan Dushoff, Juliet Pulliam, Carl Pearson, Alison Galvani, Manoj Gambhir, Ben Lopman, Travis Porco, David Champredon, Spencer Fox, Laura Skrip
- International Clinics on Infectious Disease Dynamics and Data (ICI3D)
- GA Tech Conference: Modeling the Spread & Control of Ebola in W Africa





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[Bellan SE. "Use of models in study design for dynamic systems: Ebola vaccine trial design" Clinic on Dynamical Approaches to Infectious Disease Data. DOI:10.6084/m9.figshare.5687143.](#)

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AIMS

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DST/NRF Centre of Excellence in Epidemiological Modelling and Analysis



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